1999

The theory and practice of green insurance: insurance to encourage the adoption of corn rootworm IPM

Paul David Mitchell
Iowa State University

The theory and practice of green insurance:

Insurance to encourage the adoption of corn rootworm IPM

by

Paul David Mitchell

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Agricultural Economics

Major Professor: Bruce A. Babcock

Iowa State University

Ames, Iowa

1999

UMI Number: 9940227

Graduate College

Iowa State University

This is to certify that the Doctoral dissertation of

Paul David Mitchell

has met the dissertation requirements of Iowa State University

Signature was redacted for privacy.

Major Professor

Signature was redacted for privacy.

For the Major Program

Signature was redacted for privacy.

For the Graduate College

TABLE OF CONTENTS

ACKNOWLEDGEMENTS

A few words of gratitude in a dissertation that few, if anyone, will ever read hardly does justice to the most important people in my life—my wife Jennifer and my children Abigail and Isaiah. Their love and support made this dissertation and Ph.D. possible and far more sane. When the academic world became too esoteric, they kept me in touch with the most important things in life.

I also want to acknowledge and thank some (not all) of the other people that made this dissertation possible. Bruce Babcock patiently provided his time—he was available to meet with me and offer insightful comments on short notice. As head of REP and then director of CARD he also made the financial resources available to make this dissertation happen. Todd Campbell and Mark Siemers provided invaluable C++ programming expertise as I learned how to program. David Hennessy kindly jump-started my theoretical analysis when Bruce was out of town and time was short. Larry Chandler was a generous host and made the expertise of the staff at the USDA-ARS Northern Grains Insect Research Laboratory (NGIRL) available. Walt Riedell at the NGIRL kindly provided essential data that made the empirical analysis possible. Rick Hellmich graciously invited me into the academic world of entomology and Terry Hurley showed me the service that agricultural economists can provide to help solve real problems.

Lastly, I want to thank the Risk gang. Our nights of fun playing Risk greatly reduced the stress of graduate school and made for some fond memories. Membership has changed through the years and is too long to list, but I want to specifically thank Rick Winholtz for starting it all, (John) Ray Bratsch-Prince for so often being a generous host, Mike Schweyen for being such a good loser, and Dan Topf for keeping it fun.

ABSTRACT

Best management practices exist that increase profit and improve the environmental performance of agriculture by increasing input use efficiency. Nevertheless, few producers adopt these best management practices. The risks involved with the adoption and use of these new best management practices are often thought to contribute to this low adoption rate. This dissertation theoretically and empirically analyzes the potential for best management practice insurance—green insurance—to provide insurance coverage against the failure of the practice, thus substantially reducing the risks involved with its adoption and use. Best management practice insurance removes, or at least reduces, a potentially significant factor hindering the adoption of the practice.

A general model of stochastic production focused on optimal input use is developed to theoretically analyze the impact of best management practice insurance on producer incentives to adopt the practice and on optimal input use. Theoretical results are summarized in a series of propositions, but often the sign and magnitude of important effects are theoretically ambiguous, and empirical analysis is required.

A stochastic dynamic corn rootworm population model is developed to empirically analyze corn rootworm integrated pest management (IPM). Monte Carlo simulations are used to evaluate the potential for IPM insurance to encourage producers to adopt corn rootworm IPM and reduce insecticide use. Depending on the plant day and location, for producers annually applying soil insecticides, corn rootworm IPM is worth on average $10 to $7.50 per acre, not including the cost of IPM scouting, and reduces insecticide application 75% to 95%. Depending on the plant day and location, actuarially fair IPM insurance requires a premium of $2.15 to $4.50 per acre and is worth $0.30 to $0.60 per acre to

producers. Unfortunately, once the actuarially fair premium is increased to make the insurance feasible for private insurance companies to provide, producers are no longer willing to purchase the IPM insurance. This occurs because profit losses occurring when IPM fails are generally small, and thus the value to producers of the risk sharing benefits of IPM insurance is small.

CHAPTER 1: LITERATURE SYNTHESIS AND DISSERTATION OVERVIEW

1.1 Introduction

Because agricultural production is partially stochastic, inputs are often not completely consumed by the production processes and as a result generate pollution. In addition, production uncertainty affects input demands, so that producers may over-utilize inputs to manage risk, further contributing to pollution. Obvious examples include traditional non-point source pollution problems such as nutrient and chemical losses from fertilizer and pesticide use, as well as soil erosion occurring as a result of tillage. In the development and implementation of current and past programs to reduce non-point source pollution, policy makers in general have not fully taken the risk management use of inputs into account. As a result, the potential exists to develop more efficient incentive-based methods for non-point source pollution reduction.

This dissertation presents a theoretical and empirical analysis of a "green insurance" program that takes advantage of these potential efficiency gains. This green insurance provides coverage for producers who adopt production practices that use inputs more efficiently and thus generate less pollution. In addition, since production uncertainty is reduced, producers may use green insurance as a substitute for the use of inputs to manage risk, further reducing input use and pollution. As a market-based method, green insurance may provide incentives for the reduction of non-point source pollution more efficiently than subsidies. Green insurance is also more practical than current permit trading schemes developed for non-point source pollution problems.

The remainder of the dissertation is organized as follows. To motivate the work and place it in context, chapter 1 provides a synthesis of the literature on input use under production uncertainty and agricultural non-point source pollution. In addition, chapter 1 includes a motivation and overview of Integrated Pest Management (IPM) insurance for corn rootworm, the green insurance program analyzed in the empirical portion of this dissertation. Chapter 2 presents a general theoretical model of input demand under production uncertainty when an alternative production practice and green insurance is available. This model is used to analyze producer incentives to adopt the new practice and purchase green insurance, as well as the impacts on optimal input use. Chapters 3 and 4 describe the stochastic model of corn rootworm population dynamics. Chapter 5 discusses the results of the empirical analysis of the IPM insurance for corn rootworm based on this population model.

1.2 Problem Motivation and Literature Synthesis

1.2.1 Input Demand under Production Uncertainty

Traditionally agricultural economists have analyzed the impacts of production uncertainty on input demands by focusing on income (or yield) variability and used the Arrow-Pratt concept of risk aversion. With this approach, risk preferences matter and the standard neoclassical decision rule is modified so that the value of an input's marginal product is equated to the sum of its price and the marginal risk premium. The conditions necessary to determine the sign of the marginal risk premium and its comparative static responses to various factors became an important area of theoretical research. Pope and Kramer (1979) categorized inputs as either risk increasing and risk reducing according to how they affected the marginal risk premium, but only in the context of the Just-Pope heteroscedastic production function (Just and Pope 1978). MacMinn and Holtmann (1983) derived more general conditions that applied to all production functions by extending Leland's (1972) Principle of Increasing Uncertainty to production uncertainty. Ramaswami

(1992) derived even weaker conditions needed to sign the marginal risk premium. Loehman and Nelson (1992) explicitly incorporated risk substitution and complementarity between inputs into the analysis, and as a result were able to sign comparative static derivatives that Pope and Kramer could not.

However, focusing only on income (or yield) variability and risk aversion is only appropriate for certain specifications of the profit function. How stochastic factors enter the profit specification significantly affects the impact of risk on input demands. If profit is linear in the stochastic factors, then only risk averse firms adjust their input use in response to the uncertainty. However, if profit is nonlinear in the stochastic factors, even risk neutral firms adjust their input use to manage the risks. The Arrow-Pratt concept of risk neutrality implies neutrality only to income or profit risk. When profit is nonlinear in the stochastic factors, the willingness to pay to avoid risk and the impact of risk on input use are not solely determined by the how risk affects the variability of income.

Profits that are nonlinear in stochastic factors can occur for many reasonable specifications of production uncertainty. The resulting response of risk neutral firms to production risk has been noted by many previous studies. Just (1975) specified a two part marginal cost function, with the non-stochastic part depending on planned output and the stochastic part depending on actual stochastic yield. The response of the expected profit maximizing risk neutral firm to the uncertainty depended "...critically on the nonlinearity of marginal cost ..." (p. 351). Ratti and Ullah (1976) specified a production model with random service flows from applied inputs and, because profit was a concave function of the random variables, found that the risk neutral firm used less inputs than when service flows were non-stochastic. Antle (1983) presented various dynamic production models that result in the nonlinearity of profit in the random variables, and noted the resulting relevance of risk even for risk neural firms. For a general model of production uncertainty, MacMinn and Holtmann (1983) defined the "technological risk premium" to describe the willingness to pay for certainty, measured in terms of the input response of a risk neutral firm to production risk. Babcock and Shogren (1995) discuss a similar concept, the "production premium," that measures the willingness to pay to resolve uncertainty concerning stochastic inputs. In their empirical analysis of nitrogen fertilizer use on corn, they reported that the production premium ranges from 20-80% of the total willingness to pay for certainty for all production risk.

The primary lesson to be learned from this literature is that agricultural economists must carefully specify their models of stochastic production, so as to be true to the actual physical processes, not for the sake of econometric or theoretical convenience. Antle (1983) argues that "to increase the relevance of their models and methods, ... agricultural economists need to understand specifically how risk affects agricultural production" (p. 1099). Loehman and Nelson (1992) note that "specification of this production function should be based on physical relationships between inputs and sources of risk," (p. 220) and list such factors as weather and insects. The Just-Pope heteroscedastic production function (Just and Pope 1978) is widely used in empirical analyses because it does not impose structure on how inputs affect risk, but allows both risk reducing and risk increasing inputs (Just and Pope 1979, Love and Bucola 1991, Saha et al. 1994). However, it does impose linear production risk and those using it for empirical applications should note this property, particularly if it bears on the question addressed.

1.2.2 Effect of Crop and Revenue Insurance on Input Demand

How crop and revenue insurance affect optimal input use is becoming an important issue, particularly as policy makers rely more on insurance to achieve their goals as traditional commodity support programs are phased out. The Federal Crop Insurance Reform Act of 1994 initiated the process of improving and expanding crop insurance in the United States. New revenue insurance products such as Crop Revenue Coverage (CRC) and Revenue Assurance (RA) were developed and have become quite popular. An area-yield insurance program—Group Risk Program—has been redesigned as well. In addition, the 1994 Act repealed the Ad Hoc Disaster Assistance Program and made catastrophic coverage a required minimum for producers participating in federal programs.

Crop and revenue insurance create an additional factor that influences optimal input use. Besides considering how inputs change the marginal risk premium, optimizing producers consider how input use affects the probability and magnitude of the insurance indemnity. This second effect, the "moral hazard effect," provides incentives for input reduction, while the sign of the first effect, the "risk effect," depends on whether the input is risk reducing or risk increasing. For risk reducing inputs, both effects work in the same direction and an unambiguous reduction in optimal input use results. However, for risk increasing inputs the effects offset one another and which dominates is an empirical question.

Quiggin (1991) suggested the theoretical possibility that crop insurance could increase input use, while Ramaswami (1993) formally demonstrated it for a general stochastic production process. In addition, Ramaswami conducted Monte Carlo simulations to determine which effect dominated for nitrogen fertilizer in corn production. Crop insurance resulted in an increase of optimal fertilizer use only for low levels of coverage (<

50%) when yield variability responded positively to fertilizer use at twice the estimated rate. In a similar study, Babcock and Hennessy (1996) conducted Monte Carlo simulations with stochastic yields and prices and analyzed both crop and revenue insurance. Both types of insurance decreased the optimal nitrogen rate, with revenue insurance creating a slightly larger moral hazard effect. A negative correlation between price and yield offset the impacts of insurance and smaller reductions occurred.

Analyses based on observed producer behavior in general reach the same conclusion. Quiggin et al. (1993) estimate that crop insurance reduced expenditures on fertilizer and pesticides by 10% for U.S. corn farmers. Horowitz and Lichtenberg (1993) estimated a probit model with survey data and reported a controversial nitrogen increase of 19% and pesticide expenditure increase of 21% for U.S. corn producers purchasing crop insurance. However in a similar study, Smith and Goodwin (1996) identified probable specification errors in Horowitz and Lichtenberg's analysis and reported conventional results for the effect of crop insurance on the input use of Kansas wheat farmers.

In general the existing literature shows that, if an input is sufficiently risk increasing, it is theoretically possible for per acre input use to increase with insurance coverage. However, for important inputs such as fertilizer and pesticides used for commodity crop production, the moral hazard effect dominates any offsetting risk effects and per acre input use falls with increases in insurance coverage.

1.2.3 Effect of Commodity Programs on Input Demand

Federal commodity programs affect optimal input use because of the income support provided, as well as the acreage allocation incentives and restrictions they create. Though the Federal Agriculture Improvement (FAIR) Act of 1996 ended the target price subsidy program and its associated planting restrictions, other programs such as the loan rate program are still in place. Furthermore, subsidy programs exist in other important crop producing nations and may be re-instituted in the United States.

The analysis of the impact of commodity programs on input use has been done in a manner similar to crop insurance. The general model of Hennessy (1998) decomposes the effects of income support policies into a wealth effect, an insurance effect, and a coupling effect. These are analogous to the three effects that Ramaswami (1993) used to decompose the impact of crop insurance—a mean effect, a risk reduction effect, and a moral hazard effect. Indeed, Hennessy's model is general enough to incorporate both traditional commodity programs and insurance programs.

Hennessy derived the sufficient conditions in terms of the profit specification required to sign the comparative static effects of increasing income support on input use. The target price program and the coupled loan rate program were structured so that some inputs could reasonably satisfy the conditions needed for unambiguously increasing input use with increased income support. Monte Carlo simulations similar to Babcock and Hennessy (1996) indicated that traditional commodity programs increased nitrogen fertilizer rates 7-10% for corn production, with the insurance effect accounting for most of the increase.

The FAIR Act also removed the acreage restrictions associated with the commodity programs. On the aggregate level, the response to this new "Freedom to Farm" has been a large increase in soybean acres, a reallocation of corn acres within the Corn Belt, and decreases in wheat, sorghum and hay acres (Babcock et al. 1997). These acreage shifts imply changes in aggregate input demands due to different crop requirements.

At the individual producer level, the acreage allocation decision also affects the input use decision. The analysis of Babcock et al. (1987) indicates that ignoring the acreage allocation decision, or assuming that it occurs after the input use decision, leads to errors. Due to the specifics of their model of corn and oats production, the error for nitrogen use and land allocation was rather small, but the associated errors for welfare analysis were substantial. To prevent these errors, whole-farm models that simultaneously make acreage allocation and input use decisions are required. I am unaware of any simultaneous analysis of acreage allocation and input use that includes the effects of insurance and/or commodity programs.

The existing theoretical literature shows that the impacts of crop insurance and commodity subsidy programs on input use can be analyzed in essentially the same manner. Empirical analyses indicate that the traditional U.S. commodity programs provided incentives for increased per acre input use. Additionally, whole farm models are needed to account for the impact of acreage allocation decisions on per acre input use.

1.2.4 Non-point Source Pollution Control

Agricultural production generates non-point source pollution as a joint product or inherent externality. Agricultural producer's use of inputs for risk management and the incomplete consumption of applied inputs by stochastic production processes further increases agriculture's contribution to non-point source pollution. Given the ubiquitous nature of agriculture, non-point source pollution is the chief cause of impaired water quality in the United States (USEPA/USDA, 1990). Regulation of non-point source pollution control is difficult for several reasons. The relation between input use and pollution generation is stochastic and site-specific. Polluters and regulators cannot observe local pollution generation with reasonable accuracy. Regulators cannot observe producer behavior without incurring high costs. The aggregation of individual pollution generation into easily observed ambient pollution is a complex stochastic process. Since the nature of the problem makes command and control policies essentially unenforceable, recent federal and state legislation has focused more on using economic incentives to address the problem, (Braden et al. 1994, Malik et al. 1994, Wolf, 1995). The economic literature on non-point source pollution is vast and I will only touch on some key theoretical papers to place my work in context.

Griffin and Bromley (1982) extended the standard point source pollution externality results of economic theory to non-point source externalities and demonstrated the efficiency, under certainty and observability, of both incentive schemes and standards based on input use or pollution output. Shortle and Dunn (1986) demonstrated that at the individual firm level, under uncertainty and observability, incentives such as taxes or subsidies for management practices (including input use) are more efficient. Helfand and House (1995) analyzed the inefficiency from using uniform input policies (both standards and incentives) under spatial heterogeneity and found that they could be quite small in their model of lettuce growers in California.

Agency theory tools have been used to address the moral hazard problem resulting from unobserved producer behavior. Segerson (1988) used the results of Holmstrom (1982) to propose individual penalties on a group of producers if observed ambient pollution exceeded some specified standard. The scheme is efficient, but substantially increases the income risk of producers and collects penalties that far exceed environmental damages, so that it is not budget balancing (a problem inherent in Holmstrom's original solution).

Xepapadeas (1991) used the results of Rasmusen (1987) to solve the budget balance problem. If ambient pollution exceeds the standard, a penalty is randomly imposed on a sub-group of possible polluters and the collected money redistributed among the rest of the group. Herriges et al. (1994) corrected a significant error in his propositions. Xepapadeas (1992) further demonstrates that the static solution is no longer efficient in a stochastic dynamic context. Bystrom and Bromley (1998) show the potential reduction in information costs for regulators by using a group penalty and allowing members to trade abatement among themselves. The primary criticism of these proposals derived from agency theory is that they are politically, legally and institutionally not feasible.

Since pollution generation is difficult to observe, a pollution permit trading program is not applicable to agricultural non-point source pollution. A modified permit system of point/non-point source pollution trading has been developed, in which point source polluters pay potential non-point source polluters to change production practices (including input use) to reduce expected pollution in the area. In essence the program is an input subsidy program, with a private funding source that incurs the transaction costs of obtaining participation. But since it is market-based, it is more efficient than a uniform input subsidy. However, because of uncertainty in non-point source abatement efficiency and enforcement costs, determining the optimal ratio at which point source and expected non-point source pollution are traded is unclear (Malik et al. 1993). Other technical and institutional problems have led to the general failure of the five point/non-point trading programs currently in existence; no trades are occurring and emissions exceed ambient pollution goals (Hoag and Hughes-Popp 1997).

In general, this theoretical literature indicates that incentive-based input policies are the most efficient non-point source pollution control method. Furthermore, such policies are more practical to implement in the current institutional structure. These polices are not market based, so potential inefficiencies arise from using uniform subsides and taxes. However, these inefficiencies are potentially negligible once monitoring, enforcement and other transaction and information costs have been included.

1.2.5 Best Management Practices and Input Use

Policies intended to reduce agricultural non-point source pollution have traditionally focused on encouraging farmers to adopt best management practices (BMPs) that reduce pollution generation. Since BMPs typically involve increasing the efficiency of input use, these policies are consistent with the theoretical findings previously discussed. As an added benefit of BMPs, producer profits generally increase as a result of more efficient input use. Nevertheless, many farmers do not adopt BMPs, despite the gain in profits. Typical explanations include a lack of information concerning the BMP and its profitability; time, liquidity, labor and managerial constraints; as well as aversion to the numerous risks and changes involved in adopting new production practices (Nowak 1992, Westra and Olson 1997).

To encourage the adoption of BMPs, voluntary means have traditionally been used, such as information-based methods or financial incentives. Extension education materials and demonstration projects provide information under the assumption that informed farmers will voluntarily adopt the BMP. Financial incentive schemes include cost-sharing or simple subsidies for BMP adoption. For example the 1990 Food, Agriculture, Conservation and Trade (FACT) Act initiated the Water Quality Incentive Program for selected watersheds, under which participating farmers receive per acre subsidies or "green payments" for adopting specific BMPs such as soil nutrient testing or integrated pest management (IPM).

As an example of a state level initiative, Wolf (1995) discusses a concentrated legislative effort in Wisconsin to reduce non-point source pollution with cost sharing mechanisms for BMP adoption. Despite being well funded and rather sophisticated, institutional and enforcement problems with the program led to inadequate participation and as result, little if any improvement in ambient water quality was achieved in the priority watersheds.

Current subsidy or green payment programs have problematic inefficiencies built into them. Since they are not market based, but fixed take-it-or-leave-it subsidies, it is not possible to estimate BMP adoption as a function of payments. Furthermore, without a market, a well informed central bureaucracy is required for the programs to be efficient, which is costly to maintain and not as effective at responding to changes in local conditions. Green payments are also an expensive method to promote BMP adoption. With the take-it-or-leave-it program, Cooper and Keim (1996) estimate a subsidy of about $30 per acre is needed to get 50% of producers currently not using a split nitrogen application to adopt this BMP. To get 50% participation for other BMPs such as IPM, manure testing, or legume crediting, they estimate a green payment of $50-$60. Lastly, a green payment program creates an incentive for producers already using the BMP to quit doing so, then re-adopt the practice to obtain the green payment.

Conservation compliance requirements, initiated with the 1990 FACT Act and continued with the 1996 FAIR Act, have significantly reduced soil erosion, as intended, but are not as effective at reducing other non-point source pollutants (Babcock et al. 1997). Tweeten and Zulauf (1997) have proposed more general environmental compliance requirements, but with the end of commodity program transition payments in 2002, such a program will become too expensive to fund directly. If environmental compliance were mandated, designing a feasible policy would be difficult and the program would suffer from enforcement and institutional problems such as discussed by Wolf (1995).

The general consensus of this literature is that attracting sufficient participation to obtain significant reductions in pollution with green payment subsidy programs is prohibitively expensive. Furthermore, the political feasibility of such a program is questionable, given the likelihood of enforcement and institutional problems.

1.2.6 Green Insurance

Green insurance is insurance that encourages agricultural producers to adopt a specific BMP by providing coverage against losses occurring as a result of BMP failure, losses that may have been avoided had the status quo practices been used. Green insurance focuses on the pertinent risk factors that lead to failure of the BMP and contribute to its non-adoption. These risks can be broadly classified into three types—innovation risk, testing risk, and timing risk.

A producer must implement a new and unfamiliar production practice and modify it to the unique characteristics of his land and operation. The potential of a costly innovation error is real and aversion to this risk is cited as a reason BMPs are not adopted (Nowak 1992, ACIC 1998a). Green insurance addresses this risk by requiring that insured producers use the technical assistance and/or services of trained third parties such as certified crop consultants and approved extension agents.

Even when properly implemented, a BMP can fail. A BMP typically uses inputs more efficiently because it requires producers to first collect information concerning the true input needs of a crop. However, sampling and measurement errors make this information an imperfect signal concerning the true state of the world. As a result, the BMP can fail when it indicates that less inputs are needed than is truly the case. Green insurance provides coverage for producers against losses that occur as a result of sub-optimal input use due to testing errors.

A BMP can also fail because it typically requires postponing input applications until the crop needs the inputs and/or information has been collected. As a result, a smaller window of time exists during which inputs can be applied for optimal effectiveness. Conditions beyond the producer's control, particularly weather, can prevent input application and result in failure of the BMP. Green insurance provides coverage against this timing risk by paying indemnities when weather prevents timely input application or otherwise results in sub-optimal input use.

Green insurance is an incentive based input policy, and as such has the previously discussed theoretical advantages of these policies. An additional advantage green insurance has over subsidy or tax schemes is its greater cost efficiency for providing incentives for BMP adoption. A subsidy is paid regardless of the outcome of the BMP, while green insurance only pays when a BMP fails. As long as the expected indemnity minus the premium is less than the subsidy, green insurance is on average more cost efficient for a risk neutral insurer. In addition, since it provides risk sharing benefits, green insurance provides welfare gains that subsidies do not. Thus a dollar spent on green insurance provides greater incentives for BMP adoption and welfare gains than a dollar spent on a green payment.

Green insurance also attains the efficiency benefits of a market based policy. As a market product, producers choose their level of coverage and set some of its terms. Thus the insurance more effectively fulfills their risk management needs than a uniform policy or a take-it-or-leave-it offer. The market allows producer's private information concerning the site-specific characteristics of their land and the constraints their farm operations face, as well as their own risk preferences, to provide a more efficient product. An additional benefit of green insurance over green payment subsidies is that no longer are there incentives for those currently using the BMP to stop and re-adopt in order to obtain program benefits

Green insurance also compares favorably to crop and revenue insurance as a means to reduce non-point source pollution. As previously discussed, crop and revenue insurance generally lead to a reduction in per acre input use because of the combined moral hazard and risk effects. Green insurance also creates analogous effects that reduce input use. The moral hazard effect leads to a reduction in input use, since it increases the likelihood of receiving a payment. Also producers can use green insurance as a substitute for inputs to manage risk, further reducing input use. Additionally, green insurance has an adoption effect that crop and revenue insurance do not have. By adopting the BMP, producers adopt a more input-efficient technology and reduce input use.

How the net effect of green insurance compares to the net effect of crop and revenue insurance is an empirical question that must be explored. Intuitively, green insurance should reduce input use and non-point source pollution more than crop or revenue insurance. Crop and revenue insurance aggregate many of the risks a producer faces and pay indemnities only when, as a whole, the various risks result in an outcome below some threshold. This aggregation in useful to achieve producer welfare goals, but to provide incentives for BMP adoption and pollution reduction, targeting the pertinent risks is more efficient.

An additional advantage of green insurance is that private companies may find it profitable to provide the insurance, without the need of premium subsidies as crop and revenue insurance require. Some green insurance products could potentially be provided in a manner similar to current hail and fire insurance policies, which are a common part of crop risk management strategies, but not federally subsidized.

Given this general description, green insurance seems to be a potentially useful method to reduce agricultural non-point source pollution, with several advantages over current and proposed control policies. Green insurance is a more efficient and cost effective manner to provide incentives for reducing non-point source pollution control, because it focuses on the pertinent production risks and explicitly takes the risk management aspect of input use into account. However, a more formal theoretical and empirical analysis is required for a rigorous assessment of green insurance.

1.3 Overview of Green Insurance for Corn Rootworm IPM

The idea of insurance for adoption of new or more efficient agricultural technologies is not a new idea, at least for IPM (Turpin 1974). However, recently there has been a renewed interest in developing and marketing such insurance products by insurance companies, the seed industry, government agencies, and academics. Among the products proposed or studied have been insurance for no-till farmers, insurance for various nutrient management BMPs, IPM insurance, and refuge insurance for producers planting transgenic crops. Indeed, new insurance products of this sort were offered for the first time during 1998 and others are currently being developed (ACIC 1998b). This dissertation presents an empirical analysis of a green insurance program for corn rootworm IPM. In this chapter, an overview of corn rootworm biology and IPM for corn rootworm control is first presented, followed by a general discussion of IPM insurance.

The northern corn rootworm (*Diabrotica barberi* Smith and Lawrence) and the western corn rootworm (*Diabrotica virgifera virgifera* LeConte) together comprise the most damaging insect pest to corn in the United States. In general, both species are found wherever corn is grown, but are centered in the Corn Belt where they are prevalent (Chiang 1973). Managing corn rootworm accounts for the largest expenditure for insect control in corn production (Pike et al. 1995), with Metcalf (1986) estimating the annual cost of yield losses and control expenses at $1 billion. Historically corn rootworm has been a pest for non-rotated corn acreage and the traditional management practice has been the application of soil insecticides. Becker and Stockdale (1980, cited in Foster and Tollefson 1986) report that in 1979, soil insecticides were applied for corn rootworm control to 6.7 million acres of corn in Iowa (approximately 50% of total corn acreage). More recently, Pike et al. (1991, cited in Gray and Steffey 1998) report that in Illinois, 2.5 million acres (approximately 25% of total corn acreage) of non-rotated corn are treated annually with soil insecticides. Historically, the most common types of soil insecticides applied have been organophosphates and carbamates, though others have recently become available. As a required by the Food Quality Protection Act of 1996 (FQPA), the EPA has begun reassessing the registration and safety standards for pesticides in these two groups. The new more stringent risk criteria established by the FQPA have led the EPA to consider banning these pesticides.

Adult corn rootworm emerge from their underground pupal cells over a period of about six weeks, beginning as early as late June. Adults feed on corn silk, pollen, leaf tissue, and exposed kernels, and may cause economic damage, especially for seed corn production. Mating begins soon after emergence and oviposition (egg laying) starts 10-12 days after emergence. Females deposit eggs in soil from mid summer to as late as September, primarily in corn fields. The eggs lie dormant (diapause) in the soil through winter and hatch the next spring. Hatch can occur as early as mid-May in warm years, or as late as mid-June for cool years. Larvae feed exclusively on corn roots; if none are found the larvae die. The larvae pass through three stages (instars), with first and second instars tunneling from root tips to the plant base and leaving identifiable feeding scars. Third instars typically feed on large roots near the stalk and damage brace roots that enter the soil. Third instars then pupate in earthen cells and emerge as adults beginning as early as late June. For a more detailed overview of the corn rootworm life cycle, see Chiang (1973) and Krysan (1986).

Larval feeding on roots causes the most significant damage from corn rootworm. Root damage reduces the flow of water and nutrients up the plant stalk, thus reducing plant vigor and yield. Feeding scars also allow entry of pathogenic fungi into roots, further reducing yields. Furthermore, damage to large roots causes corn plants to fall over (lodge), particularly under windy or wet conditions. Lodging reduces yields, because lodged plants do not perform as well as non-lodged plants for several reasons (Spike and Tollefson 1991). Lodging also makes harvesting more expensive, since the combine must move more slowly to pick up lodged plants, and additional yield reduction occurs because some ears cannot be harvested from severely lodged plants.

Traditionally, rotations were an effective means of corn rootworm control, since eggs were laid exclusively in corn fields. The following year, eggs would hatch and the larvae would not find corn roots and die. However, both northern and western corn rootworm have become increasingly adapted to common two-year corn rotations. In the western Corn Belt, the northern corn rootworm has developed an extended diapause, in which eggs remain dormant for two winters and larvae hatch occurs when corn is again planted in a field. In 1962 in Minnesota, Chiang (1965) found 2% of field collected northern corn rootworm eggs hatched after two winters. By the 1980's Krysan et al. (1984) found as many as 40% of eggs hatched after two winters in South Dakota. More recently, the extended diapause has been reported in Iowa as well. In the eastern Corn Belt, variant populations of western corn rootworm have adapted to common corn rotations by laying their eggs in soybean and alfalfa fields. Initially reported in the early 1990's in Illinois and Indiana (Gray et al. 1996, cited in Gray and Steffey 1998), by the summer of 1998 the variant population had spread to southern Michigan and western Ohio (Michigan State University Extension 1998). As a result of these adaptations of both species, application of soil insecticides on rotated corn is becoming more common.

The recommended Integrated Pest Management (IPM) technique for corn rootworm control is to scout for adults during July and August (since other stages of the pest live underground and are difficult to sample). If the maximum number of observed adults per plant exceeds the economic injury level (EIL), treatment with a soil insecticide is recommended for corn planted in the field the following spring. The typical EIL recommended by entomologists is one adult corn rootworm beetle per plant. However, using this IPM strategy is not without risks. Stamm et al. (1985) found that using this EIL had a prediction accuracy of 80% and 50% in the two locations in Nebraska studied. Using a lower EIL, between 0.75 to 0.90 beetles per plant, improved prediction accuracy to greater than 90%. Foster et al. (1986) used an expected profit maximization criterion to calculate the value of the scouting information for several fields in three counties in Iowa. They concluded that scouting has zero expected value, since the information does not change the ex ante probability estimates of economic losses enough to justify collecting the information or to justify not applying soil insecticide. Therefore, they conclude that the optimal strategy for corn rootworm control in Iowa is to always apply soil insecticide at plant. Naranjo and

Sawyer (1989b) use a simulation model built from laboratory and field data and conclude that the optimal EIL changes depending on the planting date, day of peak corn flowering, and the general temperature pattern of the year (above average, average, below average). Nevertheless, extension entomologists continue to support scouting and the use of a simple EIL (not necessarily one), and professional crop consultants use EIL's as well (Gray and Steffey 1997).

The green insurance program analyzed in chapter 5 encourages producers to adopt IPM for corn rootworm control by removing some of the risk associated with the use of IPM. Corn rootworm damage is typically assessed by the use of the root rating system, either on a scale of 1-6 or a scale of 1-9 (Mayo 1986), or by the percentage of the corn stand lodged. Yield loss due to corn rootworm damage is correlated with the observed root rating and the lodging. When IPM scouting indicates that soil insecticide is not required, producers can purchase green insurance coverage and follow this IPM recommendation. Later, if a producer believes that significant corn rootworm damage has occurred (because the IPM recommendation failed), the insurance pays an indemnity based on the observed root rating and/or lodging. The specific details of the production process and insurance, as well as the results of the analysis, are presented in chapter 5.

CHAPTER 2: THEORETICAL ANALYSIS OF GREEN INSURANCE

2.1 Introduction

This chapter presents a general model of stochastic production for use in the theoretical analysis of BMP adoption and green insurance. The optimization program for a representative producer is developed for various scenarios, then used to analyze the impact of BMP adoption and green insurance on adoption incentives and optimal input use. Results are summarized in several propositions, with examples from corn production used to provide intuition.

2.2 General Model of Stochastic Production with a BMP and Green Insurance

2.2.1 Model Description and Sequence of Events

The representative producer modeled here manages a homogeneous unit of land normalized to one acre, all devoted to the production of a single crop. All profit is converted to physical output by normalizing the crop price to one and all other income and wealth is ignored. Per acre profit is denoted π and the producer derives utility from this profit according to the function $u(\pi)$, where $u' > 0$ and $u'' < 0$.[1] The profit specification depends on the production technology used and whether insurance is purchased. However, for all specifications, a production process transforms a purchased input x and naturally occurring stochastic inputs θ and ε according to the crop growth function $f(x, \theta, \varepsilon)$, where $f_x > 0$, $f_{xx} \leq 0$, $f_\theta > 0$, and $f_\varepsilon > 0$.[2] No assumptions are made concerning the other derivatives of $f(x, \theta, \varepsilon)$, but by assumption, θ and ε are independent.

---

[1] Throughout this dissertation, single and double primes indicate first and second derivatives respectively.

[2] Throughout this dissertation, single and double subscripts denote first and second partial derivatives with respect to the subscripted variable(s) respectively.

From the producer's perspective, θ is a stochastic input that can potentially be observed if the information is collected, but the information is imperfect. For example, θ can be the results of a soil nitrogen test in the spring, or the observed soil moisture before irrigation, or the nutrient value of manure from a test sample. However, these signals are imperfect measures of the true input availability, due to sampling error or other limitations of the information technology. The stochastic input ε is a random production shock that captures uncertainty from two sources—first the information technology is not able to eliminate all uncertainty concerning input availability and second final input availability is determined after information concerning θ is collected. For example, ε can be weather or soil microbial events occurring after the soil sample submitted for testing was collected, or sampling error for a manure nutrient test, or variability in soil moisture across a field.

An extended example for corn rootworm provides intuition for this general theoretical model and prepares for the empirical application presented in later chapters. Define the production function $f(x, \theta, \varepsilon)$ as the proportion of corn yield saved from (or not lost to) corn rootworm damage. Then x is the quantity of corn rootworm insecticide applied, or alternatively, the frequency of application or the proportion of acres treated. Once properly defined, the number of corn rootworm adults observed via scouting is the stochastic input θ. As the observed number of adults increases, the proportion of yield lost to corn rootworm damage increases. However, since $f(x, \theta, \varepsilon)$, the proportion of yield saved, is one minus the proportion lost, as the number of observed adults increases, the proportion saved decreases. Thus θ must be defined as the inverse (or the negative) of the observed number of adults, so that $f_\theta > 0$. Lastly, the uncertainty in corn rootworm damage not explained by the observed number of adults or eliminated by insecticide applications is captured in the random shock ε. This uncertainty can be due to events occurring between scouting and corn rootworm damage, or between insecticide application and corn rootworm damage. Alternatively, this random shock can be due to sampling error in scouting or due to variability in the application rate of insecticide, or the persistence of the insecticide in the soil, or other such factors. The main point is that several factors generate uncertainty in corn rootworm damage that are independent of the observed adults and cannot be eliminated by scouting for adults or insecticide applications.

The representative producer chooses to utilize either the status quo production technology or the BMP, and, if using the BMP, whether to purchase insurance. For these three situations, the producer chooses x as follows: (1) for the status quo production technology x is chosen without observing θ, (2) for the BMP x is chosen after observing θ, and (3) for the BMP with insurance x is chosen after observing θ and purchasing insurance. In all scenarios, the producer uses available information to choose x at an exogenous per unit cost of r. Table 2.1 summarizes the sequence of events and the profit specifications for these three scenarios.

For the status quo and BMP scenarios, realized values for the stochastic inputs θ and ε are obtained from known distributions $G(\theta)$ and $H(\varepsilon)$ respectively. If the producer uses the BMP technology, the value of θ is observed at an exogenous constant cost c. All inputs are then combined by the natural production process to determine crop output according to the function $f(x, \theta, \varepsilon)$. Lastly, profit and the associated utility are determined according to the appropriate profit specification, as reported in Table 2.1.

Table 2.1. Sequence of events for each production technology

Status Quo	BMP	BMP with Insurance
Choose x^*	-	-
θ realized	θ realized	θ realized
-	Observe θ at cost c	Observe θ at cost c
-	-	Pay premium $M(\beta)$
-	Choose $x^*(\theta)$	Choose $x^*(\theta,\beta)$
ε realized	ε realized	ε realized
-	-	s realized
$\pi(x^*,\theta,\varepsilon) =$	$\pi(\theta,\varepsilon) =$	$\pi(\theta,\varepsilon,\beta) =$
$f(x^*,\theta,\varepsilon) - rx^*$	$f(x^*(\theta),\theta,\varepsilon) - rx^*(\theta) - c$	$f(x^*(\theta,\beta),\theta,\varepsilon) - r\,x^*(\theta,\beta) - c$ $- M(\beta) + I(s,\beta)$

After producers using the BMP have observed θ, but before x has been chosen, green insurance can be purchased by paying the actuarially fair premium $M(\beta)$, where β is an exogenous index of insurance coverage such that $M' > 0$. The insurance indemnity received depends on the level of coverage β and a stochastic signal s according to the function $I(s,\beta)$, where $I_s > 0$ and $I_\beta > 0$. The signal s is an imperfect measure of yield loss due to BMP failure and realized values are obtained from the known distribution $W(s|\varepsilon)$, after the producer chooses x, but before final profit is determined. Table 2.1 summarizes the sequence of events for the production process when the BMP technology is used with green insurance coverage.

BMP failure occurs in two situations—when the BMP misleads the producer into applying too little or too much x. For the sake of argument assume that all inputs are substitutes ($f_{x\varepsilon} < 0, f_{x\theta} < 0, f_{\varepsilon\theta} < 0$); these assumptions are not maintained throughout, but used here to make the explanation clearer. When the observed value of θ is large, this indicates that a small amount of x is required. However if the realized value of ε is also small, realized output is lower than anticipated and the BMP failed because it misled the producer into applying too little x. Conversely, if the observed θ is small, a large amount of x is applied. Then if the realized ε is also large, realized output is larger than anticipated and the BMP failed because it misled the producer into applying too much x. As a result, since θ and ε are independent, BMP failure is associated with extreme realizations of ε, but does not occur with every extreme realization. Low realizations of ε are correlated with applications of too little x and high realizations of ε are correlated with applications of too much x.

For example, if θ is a measure of available soil nitrogen, when θ is high, producers apply little extra nitrogen fertilizer and vice versa. However, if the sampling error for the soil test is such that the actual soil nitrogen is lower than the test indicates, the producer applies too little nitrogen fertilizer, and conversely, if the actual soil nitrogen is higher than the test indicates, the producer applies too much fertilizer. This sampling error is captured by ε. Alternatively, events occurring after the application of fertilizer also are captured by the random shock ε. If substantial rainfall occurs after fertilization, or microbial denitrification is unusually high, the soil nitrogen available for crop growth will be lower than anticipated, and the producer would have been better off following the status quo practice of over applying fertilizer at or before planting. Conversely, unusually dry weather or substantially reduced microbial denitrification generate the opposite result—the application of unnecessary nitrogen.

Producers have been primarily concerned with input deficiencies and associated yield losses. Input surpluses are usually less costly to producers, since yield loss is minor (if it occurs at all) and typically difficult to detect. BMP failures that cause input deficiencies are more of a concern to researchers and policy makers as well, since such failures create a bad reputation for the BMP and make it less likely to be adopted. Furthermore, BMP failures resulting in over application are typically "good" failures, since such failures still often imply application rates lower than for the status quo practice. As a result, in the general theoretical model presented here, BMP failures that result in over application of the input x are ignored and the focus is on BMP failures that result in input deficiencies. Given this focus, low realizations of ε are correlated with high losses due to BMP failure and vice versa.

As an imperfect measure of yield loss due to BMP failure, the signal s must be negatively correlated with ε as well, since low realizations of ε are correlated with high losses and vice versa. An underlying joint probability density function $q(\varepsilon,s)$ describes this stochastic relationship between s and ε. Extending Bayes' theorem to the continuous case (Freund 1992), this joint density function can be factored into the product of the marginal density function of ε and the density function of s conditional on ε: $q(\varepsilon,s) = h(\varepsilon)w(s|\varepsilon)$. Alternatively, the conditional density can be derived functionally by assuming that s is a function of ε and ξ, another random variable independent of ε, such that $s = \psi(\varepsilon,\xi)$. Assume $\psi_\varepsilon < 0$ so that s and ε are negatively correlated, but note that because ξ and ε are independent, not all uncertainty in s is due to ε. The function ψ can be as simple as $s = -\varepsilon + \xi$, where ξ is white noise measurement error resulting from the technology used to measure ε. Of course, other specifications of ψ are possible, as well as other explanations for ξ, the only requirement is that not all uncertainty in s be due to ε, else s and ε are perfectly correlated. Given $s = \psi(\varepsilon,\xi)$ and the required regularity conditions on ψ, the transformation of variable technique or other such methods can then be used to obtain $w(s|\varepsilon)$, the density function of s

conditional on ε. This conditional density function captures all effects of ε on s, on the mean as well as the higher moments.

Specific signals that measure yield losses associated with BMP failures depend on the BMP. For nitrogen management in corn production, the end of season cornstalk test measures the level of nitrogen in cornstalks and indicates if the corn plant was nitrogen deficient during growth (Varvel et al. 1997, Blackmer and Mallarino 1996). Similarly, a chlorophyll test indicates if a corn plant is nitrogen deficient throughout the growing season (Varvel et al. 1997). For insect damage, various measures exist that are correlated with yield loss. For corn rootworm, the root rating measures root damage due to corn rootworm, while for European corn borer, the number of cavities per plant, or inches of tunneling per plant, are measures of damage due to corn borers. For weeds, typically some measure of weed density is used and correlated with yield losses due to competition from weeds. Other such signals exist for other crops and practices, or could be developed if the need arises.

In this model, the realized value of ε can be determined ex post from realized crop output by inverting the crop production function $f(x, \theta, \varepsilon)$ and solving for ε. However, insurance indemnities are not based on observed output because of moral hazard problems associated with such a program. Yields are difficult (and costly) to observe accurately and producers can affect observed yields in response to incentives they face. Traditional yield-based crop insurance programs are not immune to this moral hazard problem and as a result require subsidies and low levels of coverage (high deductibles) for private insurance companies to provide them. Since BMP failures generally do not result in substantial yield losses, producers would need a high level of coverage to make a yield-based green insurance worth purchasing. However, the moral hazard problem at high levels of coverage is too severe for private provision of the insurance. From an insurance provider's perspective, the ideal signal is highly (negatively) correlated with actual yield losses associated with BMP failure, but is not subject to moral hazard. If the signal is not sufficiently correlated with actual yield losses, the insurance risk reduces the value of the insurance to producers, and if the moral hazard problem is too severe, private provision is not reasonable.

2.2.2 Derivation of the Optimal Input Level for Each Production Technology

2.2.2.1 Introduction

Assuming that the representative producer maximizes expected utility, the optimization problem for each production technology is stated. First order necessary conditions that implicitly define optimal input levels for each technology are derived, as well as the associated second order sufficient conditions. These results are used for the analysis in the next sections.

2.2.2.2 Status Quo Production Technology

For the status quo production practice, the producer must choose one constant value for x that is ex ante optimal over all realizations of θ and ε. The producer determines this optimal input level x^* by solving the following expected utility maximization problem:

$$\underset{x}{Max} \int_0^1 \int_0^1 u(\pi) dH(\varepsilon) dG(\theta) \tag{2.1}$$

where $\pi = f(x, \theta, \varepsilon) - rx$ and $H(\varepsilon)$ and $G(\theta)$ are the (cumulative) distribution functions of ε and θ respectively. The first order necessary condition is:

$$\int_0^1 \int_0^1 u' [f_x - r] dH(\varepsilon) dG(\theta) = 0 \tag{2.2}$$

which implicitly defines the optimum x^*. The second order sufficient condition is:

$$\int_0^1\int_0^1 \left(u''\left[f_x - r\right]^2 + u' f_{xx}\right) dH(\varepsilon)dG(\theta) < 0 \tag{2.3}$$

which is satisfied since $u' > 0$, $u'' < 0$, and $f_{xx} < 0$ by assumption.

2.2.2.3 BMP Production Technology

The producer using the BMP knows the value of θ and must choose a decision rule $x^*(\theta)$ that is ex ante optimal over all realizations of ε. The expected utility maximizing producer determines this decision rule by solving the following optimization problem, treating θ as an exogenous parameter:

$$\underset{x}{Max} \int_0^1 u(\pi)dH(\varepsilon) \tag{2.4}$$

where $\pi = f(x, \theta, \varepsilon) - rx - c$. The first order necessary condition is:

$$\int_0^1 u'\left[f_x - r\right] dH(\varepsilon) = 0 \tag{2.5}$$

which implicitly defines the optimal decision rule $x^*(\theta)$. The second order condition is:

$$\int_0^1 \left(u''\left[f_x - r\right]^2 + u' f_{xx}\right) dH(\varepsilon) < 0 \tag{2.6}$$

which again is satisfied since $u' > 0$, $u'' < 0$, and $f_{xx} < 0$ by assumption.

2.2.2.4 BMP Production Technology with Green Insurance

The producer using the BMP who has purchased green insurance knows the values of θ and β and must choose a decision rule $x^*(\theta,\beta)$ that is ex ante optimal for all realizations of ε and s. The expected utility maximizing producer determines this decision rule by solving the following optimization problem, treating θ and β as exogenous parameters:

$$\underset{x}{Max}\int_0^1\int_0^1 u(\pi)dW(s\,|\,\varepsilon)dH(\varepsilon) \tag{2.7}$$

where $\pi = f(x,\theta,\varepsilon) - rx - c - M(\beta) + I(s,\beta)$ and $W(s|\varepsilon)$ is the (cumulative) distribution function of s conditional on ε. The first order necessary condition is:

$$\int_0^1\int_0^1 u'\left[f_x - r\right]dW(s\,|\,\varepsilon)dH(\varepsilon) = 0 \tag{2.8}$$

which implicitly defines the optimal decision rule $x^*(\theta,\beta)$. The second order condition is:

$$\int_0^1\int_0^1 \left(u''\left[f_x - r\right]^2 + u' f_{xx}\right)dW(s\,|\,\varepsilon)dH(\varepsilon) < 0 \tag{2.9}$$

which again is satisfied since $u' > 0$, $u'' < 0$, and $f_{xx} < 0$ by assumption.

The conditions stated in (2.8) and (2.9) assume that the producer cannot influence s through x by affecting its distribution. Formally, $\partial W(s\,|\,\varepsilon)/\partial x = 0$ is a necessary condition for expressions (2.8) and (2.9) to be of this form. This assumption implies that the green insurance program is not subject to a moral hazard effect, since the producer cannot affect the distribution of the indemnity received. Situations for which it may be desirable to have a green insurance program subject to a moral hazard effect are discussed later in this chapter.

2.3 Theoretical Analysis of Adoption Incentives

2.3.1 Introduction

In this section, producer incentives to adopt the BMP and purchase green insurance are examined and sufficient conditions that ensure an expected utility maximizing producer has an incentive to adopt the BMP and/or purchase green insurance are summarized in two propositions. A criterion for determining when green insurance is more cost effective than green payments for incentive provision for BMP adoption is then summarized in a third proposition. Next follows an analysis of the impact of BMP adoption and the various policy instruments on optimal input use. Determining the sign of the adoption effect is analytically intractable; however, three propositions summarize conditions that allow determination of the sign of the wealth effect, the risk effect and the moral hazard effect on optimal input use.

2.3.2 BMP Adoption Incentives

Assuming that producers maximize expected utility, a producer has an incentive to adopt a BMP if the expected utility from using the BMP technology exceeds that of the status quo technology. The optimization program expressed in equation (2.1) defines the expected utility for the status quo technology. However, the optimization program expressed in equation (2.4) only yields the expected utility for the BMP technology conditional on a specific realization of θ. This optimization program must be integrated over all possible realizations of θ to obtain the expected utility for the BMP technology. Using (2.1), define the expected utility for a producer using the status quo technology as:

$$EU_{SQ} = \underset{x}{Max}\left[\int_0^1\int_0^1 u(\pi)dH(\varepsilon)dG(\theta)\right] \tag{2.10}$$

where $\pi = f(x, \theta, \varepsilon) - rx$. Using (2.4), define the expected utility for a producer using the BMP technology as:

$$EU_{BMP} = \int_0^1\left\{\underset{x}{Max}\left[\int_0^1 u(\pi)dH(\varepsilon)\right]\right\}dG(\theta) \tag{2.11}$$

where $\pi = f(x, \theta, \varepsilon) - rx - c$.

Certainty equivalent returns (*CER*) are a money metric measure of utility under uncertainty and are defined implicitly by $u(CER) = E[u(\pi)]$. Intuitively, *CER* are the certain income required to make the producer as well off as when he or she is facing the specified uncertainty. An explicit expression for *CER* for each production technology can be obtained by inverting the utility function: $CER_{SQ} = u^{-1}(EU_{SQ})$ and $CER_{BMP} = u^{-1}(EU_{BMP})$. Next define the willingness to pay (*WTP*) to change from the status quo technology to the BMP as: $WTP_{SQ.BMP} = CER_{BMP} - CER_{SQ}$. Given these definitions, producer incentives to adopt the BMP can be summarized in the following proposition:

Proposition 1: *If BMP information collection is costless ($c = 0$), producers currently not using the BMP technology have some incentive to adopt the BMP technology. If BMP information collection is costly ($c > 0$), producers who have a positive (negative) willingness to pay—* $WTP_{SQ.BMP} > (<)\ 0$ *—have an incentive (disincentive) to adopt the BMP technology.*

Proof: For the costless information case, it must be shown that producers have at least as high an expected utility when using the BMP as when using the status quo technology, i.e. $EU_{BMP} \geq EU_{SQ}$, or $\int_0^1 \left\{ \underset{x}{Max} \left[\int_0^1 u(\pi) dH(\varepsilon) \right] \right\} dG(\theta) \geq$

$\underset{x}{Max} \left[\int_0^1 \int u(\pi) dH(\varepsilon) dG(\theta) \right]$, when $c = 0$. No formal mathematical proof is provided, but a verbal argument suffices since the it is rather intuitive. The proposition follows from the fact that the expected value of maximums must equal or exceed the maximum of expected values. See Marschak (1954) for a discussion and a formal proof. Intuitively, the proposition follows because the producer using the BMP technology has the less restricted optimization program. The producer using either production technology optimizes over the same set of functions. However, for the BMP technology the producer solves for an optimal decision rule $x^*(\theta)$, but for the status quo technology the producer is restricted to a solution that is a constant function x^*. Alternatively, note that the producer using the BMP technology can always use the status quo optimum x^* and receive the same ex ante payoff, but has the option to choose a different x in response to the observed θ and obtain a higher payoff.

For the costly information case, the proposition follows because certainty equivalent returns are a money metric for expected utility. Thus $WTP_{SQ,BMP}$ is a money metric of the expected utility increase due to BMP adoption and as such provides a monetary measure of the incentive to adopt the BMP. If $WTP_{SQ,BMP} > 0$, then $CER_{BMP} > CER_{SQ}$ and the producer obtains greater expected utility using the BMP technology and has an incentive to adopt the BMP. If $WTP_{SQ,BMP} < 0$, then $CER_{BMP} < CER_{SQ}$ and the producer obtains less expected utility using the BMP technology and has a disincentive to adopt the BMP. This completes the proof.

The $WTP_{SQ,BMP}$ provides a monetary equivalent of the incentive to adopt the BMP, however, $WTP_{SQ,BMP}$ cannot be directly compared to the cost c because of wealth effects generated by the certain cost c. As c increases, the producer has lower initial wealth, which can affect producer risk aversion. As a result, though the producer faces the same uncertain production process as when $c = 0$, certainty equivalent returns can decrease more or less than c due to the change in risk aversion. However, for two special cases wealth effects do not occur and direct comparisons between $WTP_{SQ,BMP}$ and c are possible, as summarized in Corollaries 1 and 2.

Corollary 1: *If BMP information collection is costly ($c > 0$), risk neutral producers have an incentive (disincentive) to adopt the BMP technology if the expected profit* *using the BMP technology with costless information exceeds the expected profit using the status quo technology by at least (less than) the cost c.*

Proof: Denote the expected profit for producers using the status quo technology as $E\pi_{SQ} = E[f(x^*,\theta,\varepsilon) - rx^*]$ and denote expected profit for producers using the BMP technology when $c = 0$ as $E\pi_{BMP} = E[f(x^*(\theta),\theta,\varepsilon) - rx^*(\theta)]$. Risk neutral producers maximize expected profit, so the difference in expected profit when using the two production technologies directly measures producer incentives to adopt the BMP technology. Thus when $c > 0$, if $E\pi_{BMP} - E\pi_{SQ} \geq c$, the producer has an incentive to adopt the BMP technology, and if $E\pi_{BMP} - E\pi_{SQ} < c$, the producer has a disincentive to adopt the BMP technology.

Corollary 2: *If BMP information collection is costly (c > 0), producers with preferences that exhibit constant absolute risk aversion have an incentive (disincentive) to adopt the BMP technology if certainty equivalent returns when using the BMP technology with costless information exceed certainty equivalent returns when using the status quo technology by at least (less than) the cost c.*

Proof: The assumption of constant absolute risk aversion eliminates any wealth effects generated by c because risk aversion is independent of wealth. As a result it can be shown that, since the cost c is certain, certainty equivalent returns for using the BMP technology with costly information decrease by the same amount c. Then, denoting certainty equivalent returns for the BMP technology when $c = 0$ as $CER_{BMP}|_{c=0}$, if $CER_{BMP}|_{c=0} - CER_{SQ} \geq c$, the producer has an incentive to adopt the BMP technology, and if $CER_{BMP}|_{c=0} - CER_{SQ} < c$, the producer has a disincentive to adopt the BMP technology.

In the highly restrictive case of costless information collection, producers have an incentive to adopt the BMP technology. However, information is rarely costless to obtain. As a result, the policy relevant question is whether or not the gains in certainty equivalent returns are sufficient to cover the costs of information collection. Theoretical analysis indicates that wealth effects must be taken into account, however, empirically wealth effects will probably be small and can be ignored (Hennessy 1998). The actual magnitude of the willingness to pay cannot be determined by theoretical analysis without imposing more structure in the model, rather empirical analysis specific to each BMP is required.

Furthermore, the costs represented by c must include all relevant costs to BMP adoption and use. However, accounting for all these costs is difficult and specific to individual producers. In addition to the obvious labor and capital costs of personally collecting information and/or buying an information collection technology, or the cost of paying someone to provide the information, c must include less obvious management costs of deciding what to do with the information and potential human capital investments to learn new information technologies and/or production techniques. These less obvious costs are specific to each producer and can exceed the cost of buying the information from a provider, as the work of Cooper and Keim (1996) indicates. To account for these difficult to measure costs, the empirical analysis of BMPs in this dissertation estimates the willingness to pay for the costless BMP ($WTP_{SQ,BMP}$). This willingness to pay can then be compared to estimates of the cost of BMP adoption and use, and the policy implications discussed.

2.3.3 Effect of Green Insurance on BMP Adoption Incentives

The incentives for BMP adoption (if any) provided by actuarially fair green insurance can be determined in the same manner as for BMP adoption incentives. The expected utility with green insurance and the BMP technology can be directly compared to the expected utility with just the BMP technology. The difference can be monetarized by converting expected utility to certainty equivalent returns and calculating the willingness to pay for actuarially fair green insurance. This empirical technique indicates how much producers are willing to pay for actuarially fair insurance, but requires knowing or assuming a utility function to actually implement. More generally, the various stochastic dominance criteria can be used to compare and rank the distribution of profit with and without green insurance and determine if the insurance increases producer incentives to adopt the BMP technology. However, stochastic dominance criteria cannot rank all profit distributions. Proposition 2 provides a general criterion applicable to all profit distributions that determines if the green insurance increases or decreases producer incentives to adopt the BMP technology.

Proposition 2: *Actuarially fair green insurance increases (decreases) producer incentives for BMP adoption if the marginal utility of profit (u') and the marginal indemnity received for an increase of coverage (I_β) are positively (negatively) correlated for all θ.*

Proof: The producer's optimal value function $EU^*(\theta,\beta)$ is obtained by substituting the optimal input level $x^*(\theta,\beta)$ implicitly defined by the first order condition (2.8) into the objective function (2.7):

$$EU^*(\theta,\beta) = \int_0^1 \int_0^1 u(\pi(x^*(\theta,\beta))dW(s \mid \varepsilon)dH(\varepsilon) \tag{2.12}$$

where $\pi(x^*(\theta,\beta)) = f(x^*(\theta,\beta),\theta,\varepsilon) - rx^*(\theta,\beta) - M(\beta) + I(s,\beta)$. If this optimal value function monotonically increases in β, then producers prefer green insurance with any level of coverage ($\beta > 0$) to using the BMP without green insurance ($\beta = 0$). Assuming that all necessary functions are differentiable, this reduces to determining the sign of the partial derivative $\partial EU^*(\theta,\beta)/\partial\beta$. However, because θ is stochastic, equation (2.12) and this partial derivative must be integrated over θ. The sign of the derivative is found to be the same for all realizations of θ, so that integrating over θ does not change its sign.

Partially differentiate (2.12) with respect to β and rearrange to obtain:

$$\partial EU^*(\theta,\beta)/\partial\beta = \int_0^1\int_0^1 u'[(f_x - r)\partial x^*(\theta,\beta)/\partial\beta + I_\beta - M_\beta]dW(s\mid\varepsilon)dH(\varepsilon)$$

$$= \partial x^*(\theta,\beta)/\partial\beta \int_0^1\int_0^1 u'(f_x - r)dW(s\mid\varepsilon)dH(\varepsilon)$$

$$+ \int_0^1\int_0^1 u'(I_\beta - M_\beta)dW(s\mid\varepsilon)dH(\varepsilon)$$

The first order condition (2.8) indicates that the first term is zero. Furthermore, since the insurance is actuarially fair:

$$M(\beta) = \int_0^1\int_0^1 I(s,\beta)dW(s\mid\varepsilon)dH(\varepsilon)$$

$$\partial M(\beta)/\partial\beta = M_\beta = \int_0^1\int_0^1 I_\beta dW(s\mid\varepsilon)dH(\varepsilon)$$

This reveals that the term $(I_\beta - M_\beta)$ is simply I_β minus its expected value $E[I_\beta]$, so that the derivative can be expressed as

$$= \int_0^1\int_0^1 u' I_\beta dW(s\mid\varepsilon)dH(\varepsilon) - E[I_\beta]\int_0^1\int_0^1 u' dW(s\mid\varepsilon)dH(\varepsilon)$$

which is simply the covariance of u' and I_β in s and ε, so that

$$\partial EU^*(\theta,\beta)\Big/\partial\beta = Cov_{s,\varepsilon}(u', I_\beta) \tag{2.13}$$

Furthermore, the derivative maintains the same sign for all realizations of θ, since $u' > 0\ \forall\theta$ and I_β is independent of θ, so that the integral over θ is not required. Thus, if u' and I_β are positively correlated, the covariance is positive and producer expected utility increases in β for all realizations of θ and values of β, including $\beta = 0$, which completes the proof.

Intuitively, the criterion requires that the indemnity schedule be constructed so that when profit realizations are lower than expected (implying higher than expected marginal utilities), that I_β, the marginal increase of the indemnity for increased coverage, also be higher than expected. In other words, when "bad" profit outcomes occur, the insurance program is such that returns to increasing insurance coverage are higher as well. However, finding reasonable sufficient conditions that imply this in the context of the model here proved to be difficult due to offsetting effects. What follows is first a discussion of the intuition behind these offsetting effects, then a mathematical analysis that arrives at the same conclusion—because the effects are offsetting, empirical analysis is required to determine which effect dominates for any specific BMP and green insurance program.

Since θ is independent of ε and s, and β is fixed exogenously, s and ε are the only random variables that affect u' and I_β simultaneously and thus determine their correlation. At first, the correlation of s and ε (or equivalently, the conditioning of the density function of s on ε) is ignored, then included in the analysis for easier explanation.

The effect of an increase of the signal s on the marginal indemnity I_β depends on the sign of $I_{\beta s}$, which depends on how the green insurance program is designed. It seems reasonable to assume that the indemnity scheme is designed so that $I_{\beta s} > 0$. This implies that an increase of the realized signal s increases the marginal indemnity for an increase of coverage β, or alternatively, an increase in coverage increases the marginal indemnity received for an increase of the realized signal. For example, if $z(s)$ is the expected profit lost given the observed signal s and $\beta \in [0,1]$ is the proportion of this loss paid as an indemnity, then $I(s,\beta) = z(s)\beta$. Then, if the expected loss increases in the signal s, $z' > 0$ and $I_{\beta s} > 0$. Alternatively, if the insurance is constructed so that $I_{\beta s} = 0$, then I_β depends only on β and no longer covaries with u', so that changing the level of coverage does not affect the producer's expected utility and the producer has no incentive to purchase the insurance.

First assuming that s and ε are not correlated, then u' and I_β only covary in s. If $I_{\beta s} >$ 0, then an increase in s implies an increase in I_β. Also, an increase in s implies an increase in the indemnity, which increases profit and thus u' decreases since utility is concave in profit. Thus I_β and u' have a negative covariance in s when s and ε are not correlated.

Accounting for the negative correlation between s and ε implies that the increase in s is accompanied by a decrease in ε. The direct effect of a decrease in ε is to decrease profit and thus increase in u'. Thus including the negative correlation between s and ε reveals offsetting effects on u'. The tradeoff is that an increase in the signal s implies an increased indemnity and an associated decrease in marginal utility, but this increase in s is also accompanied by a decrease in ε, implying less income from crop production and thus an increase in marginal utility. The producer must tradeoff income from the indemnity and income from crop production, with the technology and the insurance program imposing constraints on the tradeoff.

The derivatives of u' and I_β in ε and s reveal with formal mathematical analysis the offsetting effects that determine the covariance. The four derivatives are:

$$\frac{\partial}{\partial\varepsilon}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I_\beta w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I_\beta w_\varepsilon(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I_\beta w(s\,|\,\varepsilon)h_\varepsilon(\varepsilon)\,ds\,d\varepsilon \tag{2.14a}$$

$$\frac{\partial}{\partial s}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I_\beta w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I_{\beta s} w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I_\beta w_s(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon \tag{2.14b}$$

$$\frac{\partial}{\partial\varepsilon}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u' w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u'' f_\varepsilon w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u' w_\varepsilon(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u' w(s\,|\,\varepsilon)h_\varepsilon(\varepsilon)\,ds\,d\varepsilon \tag{2.14c}$$

$$\frac{\partial}{\partial s}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u' w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u'' I_s w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u' w_s(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon \tag{2.14d}$$

Further assumptions concerning the distributions of s and ε are helpful before attempting to determine the signs of (2.14a-d). Assume that s has a unimodal distribution and that an increase in ε shifts the distribution to the left such that the original distribution with the smaller ε has a lower mean, but all other moments remain unchanged. This assumption is consistent with negative correlation between s and ε, and implies that w_ε is positive for low values of s, crosses the axis once, and is negative for high values of s. Also note the following result: $\int_{-\infty}^{\infty} w_\varepsilon(s\,|\,\varepsilon)ds = \frac{\partial}{\partial \varepsilon}\int_{-\infty}^{\infty} w(s\,|\,\varepsilon)ds = \frac{\partial}{\partial \varepsilon}1 = 0$, which also holds for the integrals of $h_\varepsilon(\varepsilon)$ and $w_s(s\,|\,\varepsilon)$ over ε. Lastly, assume that ε is distributed unimodally so that h_ε is positive for low values of ε, crosses the axis once, then is negative for high values of ε.

Even these assumptions do not allow a priori determination of the sign of (2.13), though the signs of some of (2.14a-d) can be determined. For example, since I_β is positive and increasing in s, the first term of (2.14a) is negative and, since I_β is independent of ε, the second term is zero, so that (2.14a) is negative. However, the sign of (2.14c) is ambiguous. Since $f_\varepsilon > 0$ and $u'' < 0$, the first term is negative, but since u' is positive and decreasing in s and ε, the second term is positive, and the sign of the third term is ambiguous. As a result, how I_β and u' are correlated in ε is theoretically ambiguous and the must be determined empirically. Similar results occur for (2.14b) and (2.14d) so that again the correlation in s is ambiguous and requires empirical analysis.

Because of offsetting theoretical effects, the sign of the covariance between u' and I_β cannot be determined a priori with standard assumptions. The issue reduces to producer preferences and the trade off between income from crop production and insurance indemnities imposed by the technology and insurance program. As a result, empirical analysis of each specific green insurance program for each BMP is required to determine whether the insurance increases producer incentives to adopt the BMP. Such analysis determines if a proposed green insurance product is worth developing further, or what research needs to be done to make it worth developing. An empirical analysis of this sort is the subject of chapter 5.

2.3.4 Green Payments versus Green Insurance for Incentive Provision

This section addresses the policy relevant question of how a green payment program compares to a green insurance program in terms of incentive provision for BMP adoption. Conditions to ensure that green insurance is superior to green payments are summarized in a proposition, but determining if these conditions are satisfied for a particular program requires empirical analysis.

The actuarially fair green insurance program assumed thus far is not realistic, since administrative and adjustment costs have not been included, nor has the requirement that the insurance generate normal profits for the provider (assuming a competitive insurance industry). Insurance providers cover these additional costs and obtain normal returns by adding a "load" to the actuarially fair premium. In the model here, this load is a fixed value of d, so that the actuarially feasible premium is $M(\beta) + d$, while the actuarially fair premium is $M(\beta)$.

A green payment program pays producers a direct subsidy for adoption of a specific BMP. In practice, these green payments are typically cost share subsidies that pay pre-specified proportions of the estimated cost of implementing the BMP. In the model here, this payment is a fixed amount g.

Before developing the next proposition, additional notation requires definition. Use (2.7) to define the expected utility for producers using the BMP technology who have purchased actuarially feasible green insurance as

$$EU_{GI} = \int_0^1 \left\{ \underset{x}{Max} \left[\int_0^1 \int_0^1 u(\pi) dW(s \mid \varepsilon) dH(\varepsilon) \right] \right\} dG(\theta) \tag{2.15}$$

where $\pi = f(x, \theta, \varepsilon) - rx - c - M(\beta) - d + I(s,\beta)$. Denote certainty equivalent returns for this producer as $CER_{GI} = u^{-1}(EU_{GI})$. Lastly, denote the willingness to pay for actuarially feasible green insurance for producers already using the BMP technology as $WTP_{BMP,GI} = CER_{GI} - CER_{BMP}$.

Given these definitions, conditions when green insurance is superior to green payments for providing incentives to adopt a BMP are summarized in Proposition 3

Proposition 3: *If producers adopting the BMP technology have a positive willingness to pay for actuarially feasible green insurance—$WTP_{BMP,GI} > 0$, this $WTP_{BMP,GI}$ is an additional incentive for BMP adoption provided by green insurance and to provide an equivalent incentive with a green payment subsidy requires positive government expenditure.*

Proof: By definition, $WTP_{BMP,GI} = CER_{GI} - CER_{BMP}$ is the difference between certainty equivalent returns for the producer using the BMP technology with and without insurance, and as such is a monetary measure of the increase in producer incentives to adopt the BMP. If $WTP_{BMP,GI} > 0$, green insurance provides an additional incentive and if $WTP_{BMP,GI} < 0$, it provides a disincentive.

Because the insurance is actuarially feasible, it can be privately provided and does not require any form of governmental support in the form of premium subsidies. It is possible to provide an equivalent adoption incentive with a green payment, but this requires some positive government expenditure. Use (2.4) to define the expected utility for producers using the BMP technology and receiving a per acre green payment of g as

$$EU_{GP}(g) = \int_0^1 \left\{ \underset{x}{Max} \left[\int_0^1 u(\pi) dH(\varepsilon) \right] \right\} dG(\theta) \qquad (2.16)$$

where $\pi = f(x, \theta, \varepsilon) - rx - c + g$. Denote certainty equivalent returns for this producer as $CER_{GP}(g) = u^{-1}(EU_{GP}(g))$. Note that if the green payment is zero, the producer has exactly the same optimization problem as when using the BMP without green insurance or a green payment, so that $EU_{GP}(0) = EU_{BMP}$ and $CER_{GP}(0) = CER_{BMP}$. If $WTP_{BMP,GI} > 0$, then $CER_{GI} > CER_{BMP}$, and thus for a green payment to achieve the same willingness to pay as green insurance requires changing g to increase CER_{GP} until it equals CER_{GI}. Because g enters the profit specification additively and is certain income, an increase in g increases mean profit, but leaves the other moments unchanged. As a result, the new profit distribution first order stochastically dominates the original profit distribution and producers with a positive marginal utility of income ($u' > 0$) obtain greater expected utility with the new profit distribution (see Hirshleifer and Riley's (1992) Ranking Theorem I). Therefore, if $g > 0$, $CER_{GP}(g) > CER_{GP}(0)$ and there exists some $\hat{g} > 0$, such that $CER_{GP}(\hat{g}) = CER_{GI}$. As a result, to provide an equivalent BMP adoption incentive with a green payment requires a positive subsidy of $\hat{g} > 0$. This completes the proof.

Just as in Proposition 1 with the cost c, a subsidy g that is certain changes producer wealth, which can change producer risk aversion, which then affects certainty equivalent returns. Indeed, receiving a subsidy g can change certainty equivalent returns to such an extent that a producer who previously had a $WTP_{BMP,GI} > 0$, can, after receiving a subsidy, have a $WTP_{BMP,GI} < 0$ and vice versa. For example, if producer preferences exhibit decreasing absolute risk aversion (DARA), receiving a premium subsidy increases wealth and reduces risk aversion. If this wealth effect on risk aversion is sufficient, a producer who previously had a positive willingness to pay for actuarially feasible green insurance may now have a negative willingness to pay. As a result, the subsidy would provide more incentive for BMP adoption if it were given as a cost-share subsidy and did not require the purchase of green insurance. The opposite result is possible with preferences that exhibit increasing absolute risk aversion.

Potential wealth effects caused by receipt of a subsidy preclude simple conclusions concerning the relative effectiveness of subsidies spent as either premium or cost-share subsidies. These wealth effects are theoretical realities, but likely are empirically insignificant for realistic cost-share and/or premium subsidies in agricultural production (Hennessy 1998). However, if preferences exhibit constant absolute risk aversion (CARA), risk aversion is independent of wealth and all wealth effects from subsidies are zero. This leads to Corollary 3:

Corollary 3: *If producers adopting the BMP technology have a positive willingness to pay for actuarially feasible green insurance—$WTP_{BMP.GI} > 0$—and preferences exhibit constant absolute risk aversion, a premium subsidy for the purchase of green insurance provides more incentive for BMP adoption than an equal cost share subsidy.*

Proof: Since preferences exhibit CARA, receiving a certain subsidy g does not change $WTP_{BMP.GI}$ and certainty equivalent returns increase exactly g. Thus, certainty equivalent returns for a producer adopting the BMP and receiving a green payment g are:

$$CER_{SQ} + WTP_{SQ.BMP} + g \tag{2.17}$$

while certainty equivalent returns for a producer purchasing green insurance as part of BMP adoption and receiving a premium subsidy g are:

$$CER_{SQ} + WTP_{SQ.BMP} + WTP_{BMP.GI} + g \tag{2.18}$$

The net incentive for BMP adoption provided by the green payment is g, while for the premium subsidy, the net incentive provided is $WTP_{BMP,GI} + g$, since the premium subsidy requires the purchase of green insurance. If $WTP_{BMP,GI} > 0$, then $WTP_{BMP,GI} + g > g$, which competes the proof.

Clearly if the willingness to pay for actuarially feasible green insurance is positive—$WTP_{BMP,GI} > 0$, then green insurance provides an incentive to adopt the BMP, and does so at no cost to the government, unlike a green payment subsidy. In addition, if the wealth effects generated by a subsidy are insignificant or zero, which empirically is likely to be the case, then government expenditures on premium subsidies for actuarially feasible green insurance provide more incentive for BMP adoption than expenditures on green payment cost-share subsidies. The sign of $WTP_{BMP,GI}$ determines if green insurance is superior to green payments at providing incentives for BMP adoption. However, it is not possible to a priori sign this term, rather it is an empirical issue for each specific insurance product for each BMP. An empirical analysis of this sort is the subject of chapter 5.

2.3.5 Conclusion

This section analyzed BMP adoption incentives provided by green payments and green insurance, as well as by the BMP itself, and compared the cost efficiency of the two instruments. Proposition 1 demonstrated that in order for producers to have an incentive to adopt the BMP, the BMP must generate a sufficient increase in certainty equivalent returns to cover the cost of adoption and use. The increase in certainty equivalent returns may or may not be larger in monetary value than the cost of adoption and use, depending on preferences. Proposition 2 proved that green insurance further increases the value of the BMP if the insurance policy is structured so that marginal utility and the marginal increase in the indemnity from increased coverage are positively correlated. Lastly, as demonstrated in Proposition 3, green insurance is superior to green payments if the insurance generates a sufficient increase in certainty equivalent returns to cover the load added to the premium to make the insurance actuarially feasible and wealth effects are insignificant. However, to determine if these criteria are satisfied for the three propositions requires empirical analysis specific to the insurance product and the status quo and BMP production technologies.

2.4 Theoretical Analysis of Policy Instrument Impacts on Optimal Input Use

2.4.1 Introduction

These next sub-sections attempt to analytically determine the effect of BMP adoption and the various policy instruments on optimal input use. The change in optimal input use when switching from the status quo to the BMP technology is the adoption effect and intuitively should be negative (i.e. optimal input use decreases). Lump sum green payment subsidies generate a wealth effect that can change optimal use. Receiving green insurance coverage changes the risks a producers face, and as a result creates a risk effect that changes optimal input use. Lastly, if the level of input use affects the distribution of the insurance signal, the resulting moral hazard effect can change optimal input use. Originally the hope was to determine simple and intuitive sufficient conditions that ensured desired signs for each of these effects. However, a general conclusion of this section is that analytical results are difficult to obtain, so that empirical analysis of each specific BMP and green insurance program is required.

2.4.2 Impact of BMP Adoption on Optimal Input Use

The primary benefit of BMP adoption is that producers can increase their certainty equivalent returns by utilizing polluting inputs more efficiently, so that less pollution is generated. However, BMP adoption does not necessarily result in reduced optimal input use. For example, IPM can result in an increase in insecticide use, since producers become more aware of insect pests and are encouraged to control infestations that would otherwise remain unknown or be ignored. In addition, even if BMP adoption does reduce optimal input use, regulators want to know the magnitude of this reduction in order to estimate the reduction in pollution generation. Such information allows evaluation of the efficacy of subsidy expenditures and/or judging whether pollution reduction goals are satisfied.

In the context of the model here, the effect of BMP adoption on optimal input use reduces to determining the sign and magnitude of the difference between the expected value of $x^*(\theta)$ and x^*:

$$\int_0^1 x^*(\theta)dG(\theta) - x^* \tag{2.19}$$

The expected value of $x^*(\theta)$ is required, since producers choose x conditional on the observed θ, but θ is stochastic. Originally it was hoped an expression for (2.19) could be derived using second order approximations in a manner analogous to Hennessy and Babcock (1998), so that factors determining its sign could be identified. However, it quickly became apparent that the presence of the utility function and the uncertainty due to ε made such an analysis intractable.

To illustrate, the technique of Hennessy and Babcock requires a second order approximation of $x^*(\theta)$ around $\bar{\theta}$, the expected value of θ:

$$x^*(\theta) \approx x^*(\bar{\theta}) + (\theta - \bar{\theta})\frac{dx^*(\bar{\theta})}{d\theta} + \frac{(\theta - \bar{\theta})^2}{2}\frac{d^2x^*(\bar{\theta})}{d\theta^2} \tag{2.20}$$

Applying the implicit function theorem to the first order condition (2.5) yields

$$\frac{dx^*(\bar{\theta})}{d\theta} = -\frac{\int_0^1 \left[u'' f_\theta (f_x - r) + u' f_{x\theta}\right] dH(\varepsilon)}{\int_0^1 \left[u''(f_x - r)^2 + u' f_{xx}\right] dH(\varepsilon)} \tag{2.21}$$

The expression for the second order term is even more complex. Hennessy and Babcock assumed profit maximization as opposed to expected utility maximization, and that the new technology eliminated all uncertainty concerning the availability of inputs. As a result, their analogous expression for (2.21) is simply $-\frac{f_{x\theta}}{f_{xx}}$. Even so, their expression for (2.19)—Hennessy and Babcock equation (9), obtained by substituting in expressions for the first and second derivatives, is rather complex. For the reader's convenience, it is reported here after converting to the notation as used here:

$$\frac{1}{2f_{xx}^2}\left[2f_{x\theta}f_{xx\theta} - f_{xx}f_{x\theta\theta} + \frac{f_{xx}^2 f_{x\theta\theta}}{f_{xx} + f_{xxx}\left[x^* - x^*(\bar{\theta})\right]} - \frac{f_{x\theta}^2 f_{xxx}}{f_{xx}}\right] \tag{2.22}$$

The uncertainty due to ε does not create a significant problem, particularly if ε and θ are not correlated—the partial derivatives of the production function are replaced with the expected value in ε of the same partial derivatives. However, the presence of the utility function quickly makes expressions complex and the method of Hennessy and Babcock intractable in this context. The main point is that the sign and magnitude of (2.19) are essentially impossible to determine analytically, so that an empirical analysis of each specific BMP is required. Such an analysis is the subject of chapter 5.

2.4.3 Impact of Green Payments on Optimal Input Use

Providing producers with green payments creates a wealth effect that provides incentives for some types of risk averse producers to increase their optimal input use. This effect has been noted in other studies (e.g. MacMinn and Holtman 1983, Hennessy 1998), and in this case has important policy implications. Proposition 4 summarizes the effect of green payment subsidies on optimal input use for producers using the BMP technology.

Proposition 4: *Decreasing (constant) absolute risk aversion, $f_{x\varepsilon} < 0$, $f_\varepsilon > 0$, $f_x > 0$, and $f_{xx} < 0$ $\forall\theta$ are sufficient conditions for a green payment subsidy to decrease (not change) optimal input use.*

Proof: The producer's optimization program and associated first and second order conditions are as stated in (2.4)-(2.6), except that $\pi = f(x,\theta,\varepsilon) - rx - c + g$, where g is the exogenous and certain green payment received. The first order condition implicitly defines the optimum $x^*(\theta,g)$ and again $f_{xx} < 0$ is sufficient to satisfy the second order condition. Applying the implicit function theorem to the first order condition yields:

$$\partial x^*(\theta,g)\big/\partial g = -\frac{\int_0^1 u''(f_x - r)dH(\varepsilon)}{\int_0^1 \left[u''(f_x - r)^2 + u' f_{xx}\right]dH(\varepsilon)} \tag{2.23}$$

The denominator is the second order condition and thus is negative, so that the sign of the numerator determines the sign of the derivative. To show that the numerator is negative, fix θ at some permissible value $\tilde{\theta}$, then denote π_0 as profit when $f_x(x^*(\tilde{\theta},g),\tilde{\theta},\varepsilon) - r = 0$ and π_1 as profit when $f_x(x^*(\tilde{\theta},g),\tilde{\theta},\varepsilon) - r \le 0$. Denote the Arrow-Pratt coefficient of absolute risk aversion as $R_A(\pi)$. Since $f_x > 0$ and $f_{xx} < 0$, $\pi_1 \ge \pi_0$, and since preferences exhibit DARA, $R_A(\pi_1) \le R_A(\pi_0)$ which implies:

$$-\frac{u''(\pi_1)}{u'(\pi_1)} \le R_A(\pi_0) \tag{2.24}$$

Next, note that when $f_x - r \leq 0$,

$$-u'(f_x - r) \geq 0 \qquad (2.25)$$

Next multiply (2.24) by the left-hand side of (2.25) and rearrange to obtain $u''(\pi_1)(f_x - r) \leq -R_A(\pi_0)u'(\pi_1)(f_x - r)$. The inequality holds for all ε, since if the realized value of ε is such that $f_x - r \geq 0$, then the inequalities in (2.24) and (2.25) change direction, leaving the result unchanged. Next integrate both sides over ε to obtain

$$\int_0^1 u''(\pi_1)(f_x - r)dH(\varepsilon) \leq -R_A(\pi_0)\int_0^1 u'(\pi_1)(f_x - r)dH(\varepsilon) = 0 \qquad (2.26)$$

and note that the right-hand integral is the first order condition and equals zero. Lastly, note that (2.26) holds for all realizations of θ if $u' > 0$, $u'' < 0$, $f_x > 0$, and $f_{xx} < 0$ for all θ, which completes the proof for DARA.

For CARA, note that $R_A(\pi)$ is a constant R_A, then re-express the numerator of (2.23) as $\int_0^1 u''(f_x - r)dH(\varepsilon) = -R_A \int_0^1 u'(f_x - r)dH(\varepsilon)$ and note that the right-hand integral is the first order condition and must equal zero at the optimum. Lastly, note that the equation holds for all realizations of θ if $u' > 0$, $u'' < 0$, $f_x > 0$, and $f_{xx} < 0$ for all θ, which completes the proof for CARA.

This proof extends Sandmo's (1971) method to the case of known variability in θ, which does not change the essential result—that the wealth effect of a lump sum subsidy reduces optimal input use if preferences exhibit DARA and x and ε are substitutes (MacMinn and Holtmann 1983). Intuitively DARA seems a more realistic assumption and it has empirical support from analysis of agricultural producers' decisions (Chavas and Holt 1996, Saha et al. 1994). The policy implication is that producers who receive a green payment that is in excess of that required to get them to adopt have an incentive to further reduce their input use. Thus offering high green payments not only gets more producers to adopt the specific BMP, but also encourages those who do adopt to use even less of the polluting input. Thus the effect of BMP adoption and the wealth effect of the green payment work together to reduce overall input use, as long as producer preferences exhibit DARA. However, the actual size of this wealth effect for a particular BMP requires empirical analysis to determine if it is policy relevant. The work of Hennessy (1998) indicates that empirically, wealth effects will likely be minor for Midwestern crop production.

2.4.4 Impact of Green Insurance on Optimal Input Use

Producers change their optimal input use to respond to the change in profit uncertainty that results from insurance coverage. Insurance reduces the risk that producers face, so that they have an incentive to reduce their expenditures on risk reducing activities and to engage in riskier activities. Inputs can be a form of self-insurance (risk reducing) or a type of risky activity (risk increasing) depending on the specifics of the production process and the input. For risk increasing inputs, optimal input use increases with insurance coverage and, for risk reducing inputs, optimal input use decreases with insurance coverage. This risk effect of green insurance can offset any decrease in optimal input use resulting from BMP adoption, or work with the BMP adoption effect to further decrease optimal input use. If an input is sufficiently risk increasing, green insurance may even be counter-productive to the goal of reducing overall input use. However, several studies indicate that this is unlikely for typical crop production inputs (Ramaswami 1993, Quiggin et al. 1993, Babcock and Hennessy 1996, Smith and Goodwin 1996).

The sign of $\partial x^*(\theta,\beta)/\partial\beta$ determines the sign of the risk effect and indicates whether insurance coverage increases or decreases optimal input use. If the derivative is positive, then insurance increases optimal input use because x is a risk increasing input. Conversely, if the derivative is negative, then insurance reduces optimal input use because x is a risk reducing input. If the sign is the same for all β, then insurance has the same effect regardless of the coverage, even for $x^*(\theta,0) = x^*(\theta)$, the optimum for the producer using the BMP without insurance. However, if the sign changes, this has implications for the level of coverage that regulators prefer to achieve their goals. Proposition 5 summarizes the conditions that determine whether an input is risk reducing or risk increasing.

Proposition 5: *The input x is risk reducing (increasing), and thus actuarially fair green insurance reduces (increases) optimal input use, if* $u''(f_x - r)$ *and* $(I_\beta - M_\beta)$ *are negatively (positively) correlated for all* θ.

Proof: Apply the implicit function theorem to the first order condition (2.8):

$$\partial x^*(\theta,\beta)/\partial\beta = -\frac{\int_0^1\int_0^1 u''(f_x - r)(I_\beta - M_\beta)dW(s\mid\varepsilon)dH(\varepsilon)}{\int_0^1\int_0^1 \left[u''(f_x - r)^2 + u' f_{xx}\right]dW(s\mid\varepsilon)dH(\varepsilon)} \tag{2.27}$$

The denominator is the second order condition (2.9) and is negative, so that the sign of the numerator determines the sign of the derivative. However, the numerator can also be expressed as the covariance of $u''(f_x - r)$ and $(I_\beta - M_\beta)$ in s and ε. If the covariance is negative, then (2.27) is negative, and green insurance coverage reduces optimal input use since x is a risk reducing input. Conversely, if the covariance is positive, then (2.27) is positive and green insurance coverage increases optimal input use since x is a risk increasing input. Lastly, note that because θ is stochastic, (2.27) must be integrated over θ. However, if the covariance does not change sign for all realizations of θ, then this integral is not needed and the proof is complete.

Providing intuition for this proposition is difficult and requires additional assumptions. As with Proposition 2, offsetting effects are present as well, so that reasonable sufficient conditions that determine the sign of the covariance are difficult to find. Following the method used for Proposition 2, what follows is first a discussion of the intuition for Proposition 5, then a more formal mathematical analysis. Both reach the same conclusion—because of offsetting effects, empirical analysis is required to determine which effect dominates for any specific BMP and green insurance program.

Again s and ε are the only stochastic variables that affect $u''(f_x - r)$ and $(I_\beta - M_\beta)$ simultaneously and thus determine their covariance. For simplicity, first the correlation between s and ε is ignored, then later reintroduced. Given this, s is the only stochastic variable of concern, since $(I_\beta - M_\beta)$ is no longer affected by ε through s. Before proceeding, further structure concerning preferences is required, since the effect of s on $u''(f_x - r)$ depends on u'''. If preference exhibit DARA, this implies that $u''' > \frac{(u'')^2}{u'}$, while if preferences exhibit CARA, the inequality becomes an equality. Both cases imply that u''' is positive.

Given these assumptions, an increase in s implies an increase in the indemnity and thus in profit, which implies that u'' increases, since $u''' > 0$. In addition, $(f_x - r)$ is independent of s and does not change, so that $u''(f_x - r)$ increases as s increases. Again, if

$I_{\beta s} > 0$, an increase in s implies that $(I_\beta - M_\beta)$ increases as well. These results derived from these assumptions imply that $u''(f_x - r)$ and $(I_\beta - M_\beta)$ are positively correlated and thus insurance coverage increases optimal use of the input x. This positive risk effect occurs because s and ε are not correlated. As a result, the insurance is in essence an exogenous gamble imposed on the producer that has nothing to do with the profit earned from crop production, and an increase of β changes the gamble so that the producer faces less income risk. The producer is then willing to take on more risk in crop production by increasing output, which requires an increase in input use.

Accounting for the correlation between s and ε reveals the potential for offsetting effects, so that it is in general no longer possible to determine the sign of the covariance between the two terms. However, if $I_{\beta s} = 0$, then no risk effect exists, since s no longer affects $(I_\beta - M_\beta)$. Thus, even if changes in ε affect s through the conditional density function for s, though the resulting changes in s do affect the indemnity, they do not affect $(I_\beta - M_\beta)$.

When the correlation between s and ε is included, the previously discussed increase in s, and the associated increases in both $u''(f_x - r)$ and $(I_\beta - M_\beta)$, is accompanied by a decrease in ε. If $u''' > 0$, as is the case if preferences exhibit DARA or CARA, a decrease in ε decreases output and profit and so u'' decreases. But if x and ε are substitutes ($f_{x\varepsilon} < 0$), the decrease in ε also increases the marginal product of x, and that the combined effect is that $u''(f_x - r)$ decreases. Whether this effect dominates the effect of s on $u''(f_x - r)$ depends on the specifics of the production process, producer preferences, and the structure of the insurance program. The intuitive tradeoff is that an increase in the signal s implies an increased indemnity and an associated increase in the concavity of utility, but this increase in

s is also accompanied by a decrease in ε, implying less income from crop production and thus an decrease in the concavity of utility. In addition, the decrease in ε increases the marginal product of x, which further complicates the analysis. Again, the producer must tradeoff income from the indemnity and income from crop production, with the technology and insurance program dictating the constraints. As a result, empirical analysis is required for each specific green insurance program to determine if the risk effect generated by the insurance is positive or negative.

A formal analysis of the partial derivatives reveals the offsetting effects and the difficulty in deriving conditions that determine the sign of the risk effect. The four derivatives are:

$$\begin{aligned}\frac{\partial}{\partial\varepsilon}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(I_\beta - M_\beta)w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = &\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(I_\beta - M_\beta)w_\varepsilon(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon\\ &+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(I_\beta - M_\beta)w(s\,|\,\varepsilon)h_\varepsilon(\varepsilon)\,ds\,d\varepsilon\end{aligned} \tag{2.28a}$$

$$\begin{aligned}\frac{\partial}{\partial s}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(I_\beta - M_\beta)w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = &\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}I_{\beta s}w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon\\ &+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(I_\beta - M_\beta)w_s(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon\end{aligned} \tag{2.28b}$$

$$\begin{aligned}\frac{\partial}{\partial\varepsilon}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u''(f_x - r)w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = &\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u'''f_\varepsilon(f_x - r) + u''f_{x\varepsilon}w(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon\\ &+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u''(f_x - r)w_\varepsilon(s\,|\,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon\\ &+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u''(f_x - r)w(s\,|\,\varepsilon)h_\varepsilon(\varepsilon)\,ds\,d\varepsilon\end{aligned} \tag{2.28c}$$

$$\frac{\partial}{\partial s}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u''(f_x - r)w(s\mid\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u'''I_s(f_x - r)w(s\mid\varepsilon)h(\varepsilon)\,ds\,d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u''(f_x - r)w_s(s\mid\varepsilon)h(\varepsilon)\,ds\,d\varepsilon \tag{2.28d}$$

In a manner similar to that used for (2.14a-d), some standard assumptions concerning the distributions of s and ε could allow determination of the signs of some of the terms in equations (2.28a-d). However, the signs of all terms cannot be determined with such assumptions, or their combined sum is ambiguous. Because of these ambiguities, the sign of the covariance cannot be determined a priori with standard assumptions, but depends on the specifics of the green insurance program, the BMP technology, and producer preferences. As a result, empirical analysis of each specific green insurance program for each BMP is required to determine the sign and the magnitude of the risk effect on optimal input use. Such analysis indicates whether the resulting increase or decrease in optimal input use is sufficiently large to be policy relevant.

2.4.5 Green Insurance to Reduce Optimal Input Use

Previous sub-sections discussed the need for empirical analysis to determine the size of the adoption, wealth and risk effects. If the green payment wealth effect and the green insurance risk effect are insignificant, they may be ignored, but if they are large, either or both may have policy implications that may make one instrument superior to the other. However, there are limits to both instruments. If the adoption effect is not sufficiently large, both of these instruments may require substantial expenditures to generate the necessary additional adoption to achieve the pollution goals of regulators (Cooper and Keim 1996). Large subsidies may then make the wealth effect an important addition to the adoption effect. However, such subsidies can quickly become too costly to be politically feasible. Green insurance can be an improvement over green payments in terms of incentive provision, and thus achieve higher adoption for a given expenditure. However, it only provides a one time discrete amount of extra incentive—$WTP_{BMP,GI}$. If any additional incentives are required, it is no different than a green payment. In addition, a positive risk effect can offset or dominate any input reduction incentive provided by the wealth effect. Even if the risk effect is negative, it may not be sufficient to achieve the pollution reduction goals of regulators.

This section explores in a theoretical context another method of using green insurance to reduce optimal input use and pollution in a more cost effective manner. In section 2.2.2.4 it was assumed that the applied input x did not affect the distribution of the signal s, thus eliminating any consideration of a moral hazard effect. Most insurance requires elimination or sufficient reduction of this effect, or the insurance is not actuarially feasible. However, it may be desirable to use a signal that is not immune to this moral hazard effect as a means for regulators to achieve desired levels of pollution that cannot be achieved cost effectively with green payments or the standard green insurance program. If the moral hazard effect required to achieve regulation goals is too severe, the insurance will not be privately provided, unless it is publicly subsidized in a manner similar to current crop and revenue insurance programs. What makes these subsidies potentially more cost effective than cost share green payments or green insurance premium subsidies is that they can achieve a lower level of pollution for the same expenditure by exploiting the moral hazard effect. What factors make a moral hazard effect of the desired type possible are discussed in the rest of this section.

Assume that the level of x directly affects the distribution of the signal s, so that the relationship between s and x is not deterministic. Unlike the relationship between s and ε derived previously, because x is chosen optimally, the conditional distribution of s cannot be derived from the underlying multivariate distribution of s, ε, and x. Rather the stochastic relationship between s and x can be expressed functionally as $s = \kappa(x, \varepsilon, \zeta)$, where ζ is another random variable independent of ε and $\kappa_\varepsilon < 0$ to maintain the negative correlation between s and ε. To ensure that a moral hazard effect exists, $\kappa_x \neq 0$, but no other assumptions concerning κ are made. The function κ can be as simple as $s = -\varepsilon + x + \zeta$, where ζ is white noise from the technology used to measure ε and x affects only the mean of s. Other specifications for κ are possible in which x affects the mean negatively or nonlinearly, or affects the variance and higher moments of s. Given the function κ and the required regularity conditions, the transformation of variable technique or other such methods can be used to obtain $w(s|x, \varepsilon)$, the density function of s conditional on ε and the amount of x applied. This conditional distribution captures all the effects of both ε and x on s.

Using this new specification for the density function for s, the producer's optimization program must be re-derived. The producer who has purchased green insurance for which there is a moral hazard knows the values of θ and β and must choose a decision rule $x^{**}(\theta, \beta)$ that is ex ante optimal over all realizations of s and ε. The expected utility maximizing producer determines this rule by solving the following optimization problem, treating θ and β as exogenous parameters:

$$\underset{x}{Max} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u(\pi) w(s \mid x, \varepsilon) h(\varepsilon)\, ds\, d\varepsilon \tag{2.29}$$

where $\pi = f(x, \theta, \varepsilon) - rx - c - M(\beta) + I(s, \beta)$. The first order necessary condition is:

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u'(f_x - r) w(s \mid x, \varepsilon) h(\varepsilon)\, ds\, d\varepsilon + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u w_x(s \mid x, \varepsilon) h(\varepsilon)\, ds\, d\varepsilon = 0 \tag{2.30}$$

which implicitly defines the optimal decision rule denoted $x^{**}(\theta,\beta)$. The second order condition can be expressed as:

$$\begin{aligned}
&\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\left(u''[f_x - r]^2 + u' f_{xx}\right)w(s\,|\,x,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon \\
&+2\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u'[f_x - r]w_x(s\,|\,x,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon \qquad (2.31)\\
&+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u w_{xx}(s\,|\,x,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon
\end{aligned}$$

for which the previous conditions of $u' > 0$, $u'' < 0$, and $f_{xx} < 0$ are only sufficient to ensure that the first term is negative. For this model, (2.31) must be negative by assumption.

The first order condition (2.30) allows derivation of sufficient conditions that ensure the moral hazard effect reduces optimal input use.

Proposition 6: *If* $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u w_x(s\,|\,x,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon$ *is negative (positive), the moral hazard effect decreases (increases) optimal input use for producers using the BMP technology with green insurance coverage.*

Proof: If the producer ignores the effect of x on the distribution of s, the first order condition for this optimization problem is

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}u'(f_x - r)w(s\,|\,x,\varepsilon)h(\varepsilon)\,ds\,d\varepsilon = 0 \qquad (2.32)$$

which implicitly defines the optimal decision rule $\tilde{x}(\theta,\beta)$. Denote the implicit function defined by (2.32) as $\tilde{F}(x,\theta,\beta)$, which by definition is zero when evaluated at $x = \tilde{x}(\theta,\beta)$. Use $F(x,\theta,\beta)$ to denote the implicit function defined by (2.30) the first order condition for the producer taking the moral hazard effect into account. Substitute the decision rule $\tilde{x}(\theta,\beta)$

into $F(x,\theta,\beta)$. Since $\widetilde{F}(x,\theta,\beta)$ is the first term of $F(x,\theta,\beta)$, when $F(x,\theta,\beta)$ is evaluated at $\tilde{x}(\theta,\beta)$, the first term is zero. If $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} uw_x(s \mid x,\varepsilon)h(\varepsilon)\, ds\, d\varepsilon$ (the second term) is negative for all x, then $F(\tilde{x}(\theta,\beta),\theta,\beta)$ must be negative and if it is positive for all x, then $F(\tilde{x}(\theta,\beta),\theta,\beta)$ must be positive. Assuming that the second order condition (2.31) is negative, then $x^{**}(\theta,\beta) < \tilde{x}(\theta,\beta)$ when $F(\tilde{x}(\theta,\beta),\theta,\beta)$ is negative and $x^{**}(\theta,\beta) > \tilde{x}(\theta,\beta)$ when $F(\tilde{x}(\theta,\beta),\theta,\beta)$ is positive. This completes the proof and Figure 2.1 graphically presents the intuition.

Imposing more structure on the effect of x on the distribution of s yields a corollary to Proposition 6:

Corollary 4: *If the distribution of the signal s is unimodal and increasing the input x shifts the distribution such that the original distribution with the lower (higher) x has a higher (lower) mean and all other moments remain unchanged, the moral hazard effect decreases (increases) optimal input use for producers using the BMP technology with green insurance coverage.*

Proof: The assumptions concerning the distribution of s and the impact of increasing x on the distribution imply that w_x is positive for low values of s, crosses the axis once, and is negative for high values of s. Next note that $\int_{-\infty}^{\infty} w_x(s \mid x,\varepsilon)ds = \frac{\partial}{\partial x}\int_{-\infty}^{\infty} w(s \mid x,\varepsilon)ds = \frac{\partial}{\partial x}1 = 0$ and u is a positive and increasing function of s. Together these imply that $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} uw_x(s \mid x,\varepsilon)h(\varepsilon)\, ds\, d\varepsilon$ is negative for all x. Given this result, the conclusion follows as shown in Proposition 6.

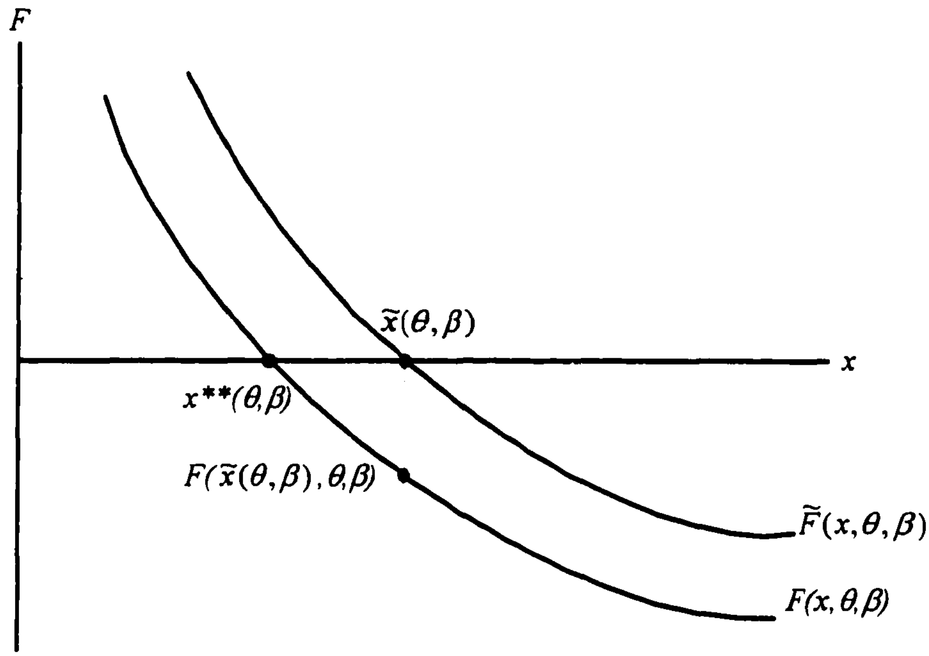


Figure 2.1. Stylized plot for Proposition 6 illustrating that if $F(x,\theta,\beta)$ is negative when evaluated at $\tilde{x}(\theta,\beta)$, then $x^{**} < \tilde{x}(\theta,\beta)$

It is theoretically possible to develop a green insurance program that exploits the moral hazard effect to obtain further reductions in optimal input use and thus pollution. All that is required is to find an insurance signal that has a distribution with the right properties, as specified in Proposition 6 and Corollary 4. This improved green insurance can attain reductions in optimal input use that the original green insurance program can only attain by increasing premium subsides to increase adoption, taking into account possibly significant wealth and risk effects. However, the magnitude of the moral hazard effect may not be sufficient to be policy relevant, or the effect may be so severe that private insurance provision is impossible without subsidies. These are empirical issues that must be addressed for each specific insurance product and production process. Later chapters present the empirical analysis of specific green insurance programs, unfortunately no analysis of green insurance products with moral hazard effects are analyzed empirically.

To create a moral hazard effect for an existing green insurance product does not necessitate finding a new signal to replace the existing insurance signal. Instead, combining the existing signal and the amount of input used can generate a new signal with the desired moral hazard effect. For example, a new signal $\tilde{s}$ could be obtained by $\tilde{s} = s + y(x)$, where $y_x < 0$ is required for the moral hazard effect to reduce optimal input use. The impact and usefulness of such a transformed signal again require empirical analysis.

2.4.6 Conclusion

This section analyzed the impact of technology adoption and the various policy instruments on optimal input use. Determining the sign and magnitude of the adoption effect was analytically intractable and thus became an empirical issue. Proposition 4 demonstrated that the wealth effect of green payment subsidies reduced optimal input use only for producers whose preferences exhibit DARA. Factors determining the sign of the risk effect caused by insurance coverage were summarized in Proposition 5. Lastly, the possibility of using a moral hazard effect to reduce optimal input use was explored and factors that determine the sign of the effect were summarized in Proposition 6 and Corollary 4.

CHAPTER 3: STOCHASTIC DYNAMIC CORN ROOTWORM POPULATION MODEL

3.1 Introduction

This chapter presents the two main components of the stochastic corn rootworm population model. First the stochastic weather generator is described, then the population model built from it is presented. Together these form the stochastic corn rootworm population model used for the economic analysis. The model was written in C++ so that multiple simulations could be conducted under a wide variety of conditions in order to understand the uncertainty associated with corn rootworm infestations.

3.2 Stochastic Weather Generation

3.2.1 Introduction

Insect population models typically assume that ambient air or soil temperatures largely determine the rate of organism development and the time needed for advancement to subsequent life stages. This generalization applies to models of all life stages, whether stochastic or deterministic (e.g. Mooney and Turpin 1976, Schaafsma et al. 1991, Fisher 1986, Jackson and Elliot 1988, Hein and Tollefson 1987). Thus any insect population model has an explicit or implicit assumption of temperature dynamics upon which it is built. A stochastic model of temperature dynamics is desirable to capture the full range of population dynamics possible due to weather variability. If only a few years of data are used, weather variability is not be sufficient to capture the full range. After searching the meteorological literature, the method described by Richardson (1981) was chosen to generate a stochastic time series of daily maximum and minimum temperatures. However, to generate daily temperatures also required generation of daily precipitation, since daily temperatures are highly dependent on daily precipitation.

The rest of this section provides a detailed description of how time series for daily precipitation and maximum and minimum air and soil temperatures are generated for use by the corn rootworm population model. In brief, the precipitation status of each day is a first-order Markov chain with two stages—wet or dry. Daily maximum and minimum air temperatures both follow a lag one autocorrelated time series, with lag zero and lag one cross correlation with the other temperature and with a mean and variance conditional on each day's precipitation status. Fourier series are used to describe the seasonal periodicity of the transition probabilities of the Markov chain, as well as the conditional means and standard deviations of maximum and minimum air temperature. Soil temperatures depend on air temperatures, but follow a lagged process due to soil heat storage and other factors. Lastly, the algorithm used to calculate degree days is presented.

3.2.2 Data Source for Estimating Precipitation and Air Temperature Parameters

EarthInfo sells the National Climatic Data Center's (NCDC) Validated Historical Daily Data on CD-ROM for hundreds of weather stations through out the United States (EarthInfo 1996). Using the accompanying software package, all observations for the daily maximum and minimum air temperature and total precipitation for weather stations in Brookings, South Dakota and Boone, Iowa were exported. For Brookings this included data from January 1, 1893 to December 31, 1994 (102 years or 37,230 days), with 441 days missing (<1.2%). For Boone the data included May 1, 1948 to December 31, 1994 (47 years or 16,837 days), with 228 days missing (< 1.35%). These data were used to estimate all parameters for stochastic temperature and precipitation generation. Unless otherwise specified, all estimation was done using the econometrics software Time Series Processor (TSP), version 4.3 (TSP International 1995).

3.2.3 Precipitation Model and Parameter Estimates

3.2.3.1 Markov Chain Model of Daily Precipitation Status

Following Richardson (1981), a first order Markov chain model was used to generate a stochastic series of wet and dry days. A first order Markov chain is defined by its transition matrix, which contains the probabilities that the process transitions from one state to the next, conditional on the current state. Typically, rows represent current states and columns represent future states for a transition matrix (Lial et al. 1998). A transition matrix must be square, since all possible states of the process must be used as both rows and columns. Furthermore, each row sums to one, since the process must end in one of the states specified by the process.

For the process modeled here, there are two states—a day is either wet or dry. The probability that a day is wet or dry is conditional on whether the previous day was wet or dry. This is summarized in the transition matrix P: $P = \begin{bmatrix} P_{dd} & P_{dw} \\ P_{wd} & P_{ww} \end{bmatrix} = \begin{bmatrix} P_{dd} & 1-P_{dd} \\ P_{wd} & 1-P_{wd} \end{bmatrix}$, where P_{dd} is the probability of a dry day following a dry day and P_{wd} is the probability of a dry day following a wet day, following the convention that row subscripts define current states and column subscripts define future states. Thus the precipitation status for any given day is completely defined by the two parameters P_{dd} and P_{wd}. However, because there are 365 days, a total of 730 parameters are required.

To reduce the number of parameters needed, the seasonal periodicity exhibited by these transition probabilities is utilized. Following the maximum likelihood method described by Woolhiser and Pegram (1979), a Fourier series was estimated for each probability. First the number of observed transitions from each state on each day are calculated and denoted a_{ij}^{n}, where $i \in \{d, w\}$ and indexes current states, $j \in \{d, w\}$ and indexes future states, and n denotes the day of the year. The log-likelihood function is:

$$\ln L(\phi \mid X) = \sum_{n=1}^{365} \begin{bmatrix} a_{dd}^{n} \ln(P_{dd}(n)) + a_{dw}^{n} \ln(1 - P_{dd}(n)) + \\ a_{wd}^{n} \ln(P_{wd}(n)) + a_{ww}^{n} \ln(1 - P_{wd}(n)) \end{bmatrix}, \tag{3.1}$$

$$P_{dd}(n) = A_d + \sum_{k=1}^{H_d} \left[C_{dk} \cos\left(\frac{nk}{K}\right) + S_{dk} \sin\left(\frac{nk}{K}\right) \right], \tag{3.2}$$

$$P_{wd}(n) = A_w + \sum_{k=1}^{Hw} \left[C_{wk} \cos\left(\frac{nk}{K}\right) + S_{wk} \sin\left(\frac{nk}{K}\right) \right], \tag{3.3}$$

where $K = 365/2\pi \approx 58.091554$ is the necessary normalizing constant, H_d and H_w are the number of harmonics estimated for P_{dd} and P_{wd} respectively, ϕ is the parameter vector of Fourier coefficients $\{A_d, A_w, C_{dk_d}, S_{dk_d}, C_{wk_w}, S_{wk_w}$, and X is the matrix of the a_{ij}^{n}, the number of observed transitions. The number of harmonics for each Fourier series was increased until the addition of a harmonic failed a Likelihood Ratio test at the 5% level of significance. The maximum likelihood estimates and standard errors are reported in Table 3.1 for Brookings and Boone, while Figures 3.1 – 3.2 illustrate the fit and smoothing of the data provided by the Fourier series.

3.2.3.2 Exponential Model of Daily Precipitation

A stochastic precipitation model was linked to the Markov chain model to determine the amount of precipitation on wet days. Several alternatives were available, but an exponential model was chosen for its simplicity (Richardson 1981). Defining R_n as the amount of precipitation for a given day n, R_n is a random draw from an exponential

Table 3.1. Fourier series coefficient estimates for the probability of a dry day following a dry day and the probability of a wet day following a dry day in Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A_d	0.7807	0.0025	0.7715	0.0037
C_{d1}	0.1031	0.0035	0.0635	0.0051
S_{d1}	-0.0094	0.0035	-0.0206	0.0053
C_{d2}	-0.0015	0.0034		
S_{d2}	0.0183	0.0036		
C_{d3}	-0.0063	0.0034		
S_{d3}	-0.0128	0.0035		
A_w	0.7712	0.0048	0.5716	0.0076
C_{w1}	0.0967	0.0071	0.0492	0.0107
S_{w1}	-0.0063	0.0064	-0.0033	0.0108
C_{w2}	-0.0034	0.0070	0.0384	0.0104
S_{w2}	0.0153	0.0065	0.0499	0.0110
C_{w3}	-0.0067	0.0068	0.0022	0.0107
S_{w3}	-0.0236	0.0067	-0.0248	0.0106

[a] See Equations (3.2) and (3.3) for coefficient definitions.
[b] Computed according to the method of Berndt et al. (1974).

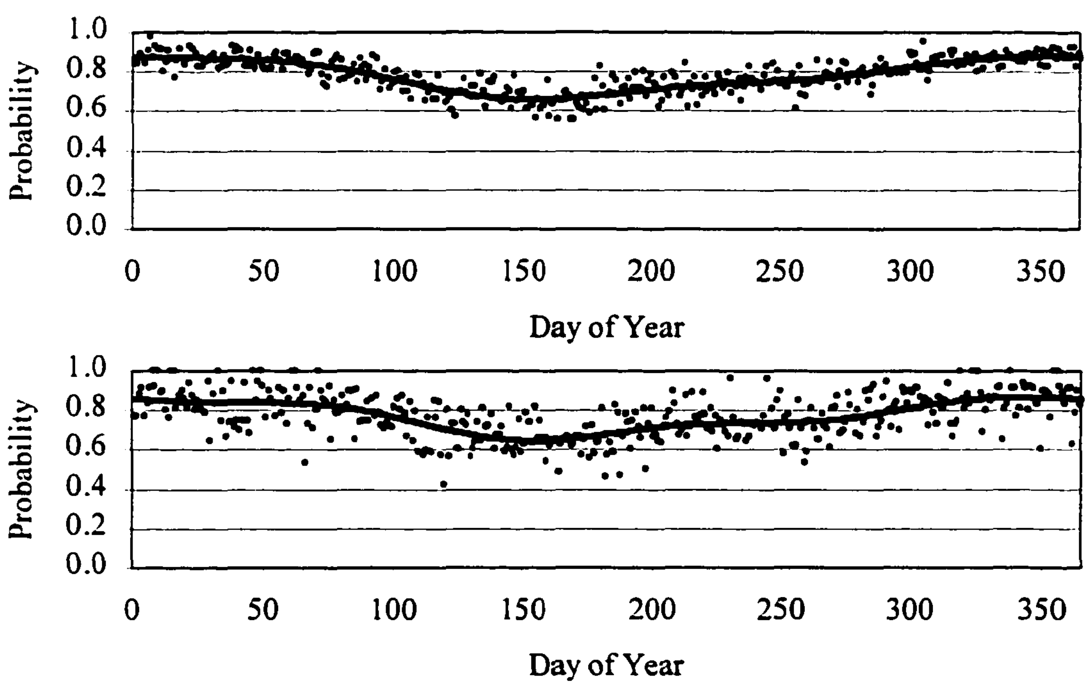


Figure 3.1. Observed and Fourier series estimated daily probability of a dry day following a dry day (top) and a dry day following a wet day (bottom) in Brookings, SD

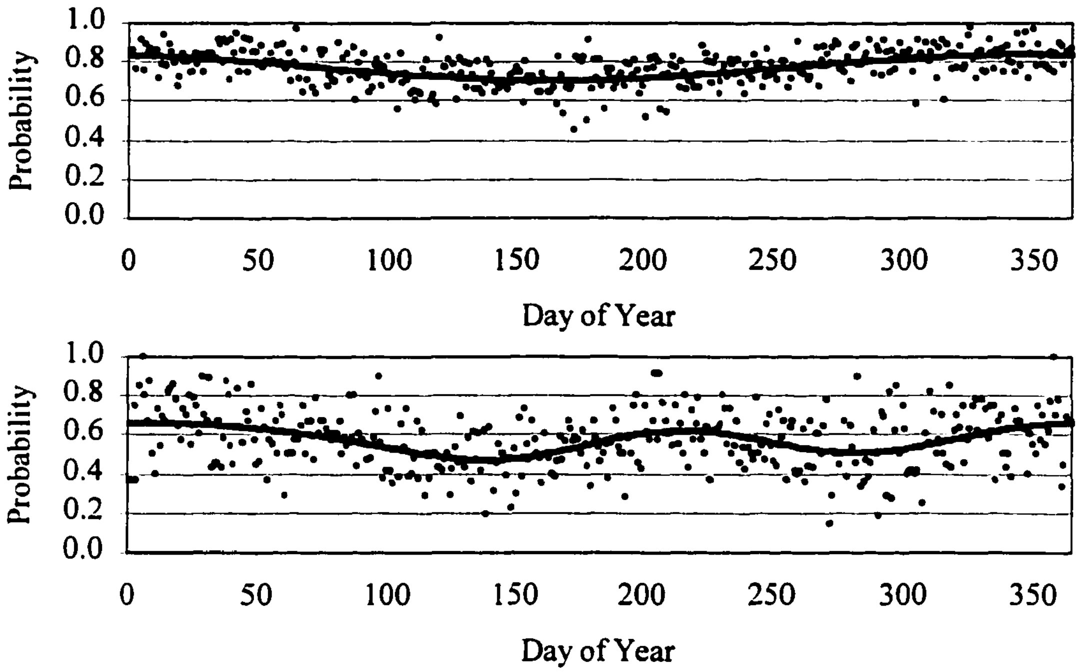


Figure 3.2. Observed and Fourier series estimated daily probability of a dry day following a dry day (top) and a dry day following a wet day (bottom) in Boone, IA

distribution with probability density function $f(R_n) = \lambda_n e^{-\lambda_n R_n}$, where the parameter λ_n is specific to each day. As with the transition probabilities, the seasonal periodicity exhibited by the λ_n was used to reduce the number of required parameters.

Following the maximum likelihood method described by Woolhiser and Pegram (1979), a Fourier series was estimated for the parameter λ. To express the log-likelihood function, define R_{ny} as the observed amount of precipitation for day n in year y, and define

$D_{ny} = \begin{cases} 0 & \text{if } R_{ny} = 0 \\ 1 & \text{if } R_{ny} > 0 \end{cases}$. Then the log-likelihood function is:

$$\ln L(\theta \mid R, D) = \sum_{n=1}^{365} \sum_{y=1}^{T} D_{ny} \left[\ln(\lambda(n)) - \lambda(n) R_{ny} \right], \tag{3.4}$$

$$\lambda(n) = A + \sum_{k=1}^{H}\left[C_k \cos\left(\frac{nk}{K}\right) + S_k \sin\left(\frac{nk}{K}\right)\right], \tag{3.5}$$

where θ is the parameter vector of Fourier coefficients $\{A, C_k, S_k\}$, T is the number of years, and H the number of harmonics. For estimation, the number of harmonics was increased until the addition of a harmonic failed a Likelihood Ratio test at the 5% level of significance. The maximum likelihood estimates and standard errors are reported in Table 3.2 for Brookings and Boone, while Figure 3.3 illustrates the fit and smoothing of the data provided by the Fourier series.

3.2.3.3 Summary of Precipitation Model

The generation of stochastic daily precipitation according to the first-order Markov-exponential model described in this section requires three steps. First, conditional on the previous day's precipitation status, calculate the probability of a dry day using the appropriate Fourier series. Second, draw a uniform random variate between zero and one and determine whether the current day is dry or wet. Third, if the day is dry, the precipitation process is complete for the day—go to the next day. Otherwise, calculate the value of λ using the appropriate Fourier series, draw the precipitation amount as an exponential random variate using this λ, then go to the next day.

3.2.4 Air Temperature Model and Parameter Estimates

3.2.4.1 Introduction

The procedure described by Richardson (1981) and Matalas (1967) was used to estimate the parameters necessary to generate a stochastic series of daily maximum and minimum air temperatures. In brief, the procedure assumes that temperatures are a continuous, multivariate, weakly stationary process with daily means and standard deviations

Table 3.2. Fourier series coefficient estimates for the parameter λ of the exponential probability density function for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	5.2815	0.0560	3.6183	0.0489
C_1	3.4095	0.0920	1.7404	0.0757
S_1	0.9470	0.0608	0.4353	0.0617
C_2	1.2737	0.0806	0.4926	0.0706
S_2	0.7630	0.0715	0.3211	0.0668
C_3	0.4884	0.0702	0.2207	0.0655
S_3	0.3548	0.0728	0.2046	0.0675
C_4	0.1094	0.0555	0.0404	0.0523
S_4	0.3386	0.0580	0.2009	0.0565

[a] See Equation (3.5) for coefficient definitions.

[b] Computed according to the method of Berndt et al. (1974).

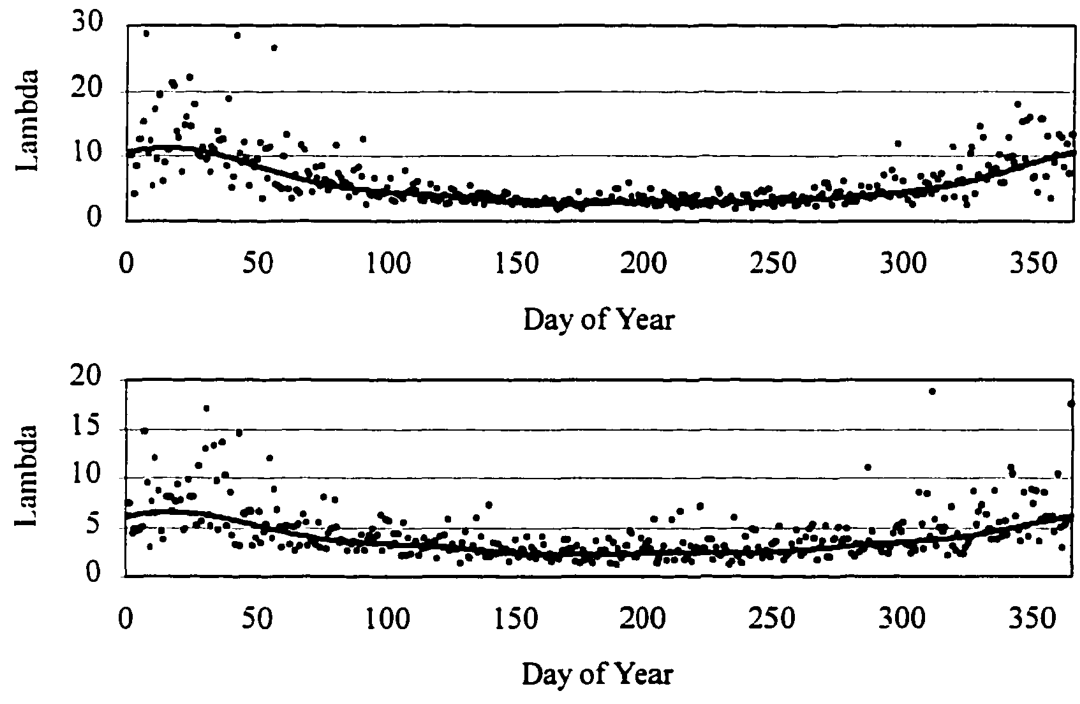


Figure 3.3. Observed and Fourier series estimated daily value of λ for the exponential probability density function for Brookings, SD (top) and Boone, IA (bottom)

conditional on the wet or dry state of the day. First separate Fourier series are estimated for the mean and standard deviation for both wet and dry days for the maximum and minimum air temperature. Next the time series of each variable is reduced to a time series of residuals by removing the daily means and standard deviations, then the serial correlation and cross correlation coefficients are calculated.

3.2.4.2 Fourier Series for Daily Mean and Standard Deviation of Maximum and Minimum Air Temperatures

The mean and standard deviation of the maximum and minimum air temperature for each day of the year was calculated separately for wet and dry days. To reduce the number of parameters required, the seasonal periodicity of the means and standard deviations was utilized. Using a least squares criterion, a separate Fourier series for each of the eight parameters was estimated—the wet and dry mean and the wet and dry standard deviation for the maximum temperature, and the same four parameters for the minimum temperature. A general formulation of the equation used for each parameter estimation is:

$$\theta(n) = A + \sum_{k=1}^{H}\left[C_k \cos\left(\frac{nk}{K}\right) + S_k \sin\left(\frac{nk}{K}\right)\right], \tag{3.6}$$

where θ is the parameter for which the Fourier series is being estimated and n is the day of the year. The coefficients to be estimated are A, the C_k and S_k, and H, the number of harmonics for the series. For each Fourier series, harmonics were increased until the addition of a harmonic failed a Likelihood Ratio test at the 5% level of significance. Coefficient estimates and standard errors for all eight Fourier series for both Brookings, SD and Boone, IA are reported in Tables 3.3 – 3.10, while Figures 3.4 – 3.11 illustrate the fit provided by the Fourier series for both locations.

Table 3.3. Fourier series coefficient estimates for the mean of the maximum air temperature on a dry day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	56.2517	0.0617	60.4045	0.0939
C_1	-29.5203	0.0872	-28.0091	0.1328
S_1	-9.4464	0.0872	-8.5034	0.1328
C_2	-3.0251	0.0872	-3.0917	0.1328
S_2	-0.6941	0.0872	-1.0609	0.1328
C_3	0.1797	0.0872	-0.2957	0.1328
S_3	-0.2027	0.0872	0.3601	0.1328
C_4	0.3126	0.0872	-0.1516	0.1328
S_4	0.8663	0.0872	0.7117	0.1328

[a] See Equation (3.6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.4. Fourier series coefficient estimates for the mean of the maximum air temperature on a wet day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	51.9957	0.1353	57.3062	0.1533
C_1	-30.5627	0.1914	-27.7780	0.2168
S_1	-9.3814	0.1914	-9.0578	0.2168
C_2	-2.2156	0.1914	-2.3425	0.2168
S_2	-0.3683	0.1914	-1.0260	0.2168
C_3	-0.0083	0.1914		
S_3	-0.6594	0.1914		

[a] See Equation (3.6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.5. Fourier series coefficient estimates for the mean of the minimum air temperature on a dry day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	31.2684	0.0552	35.7891	0.0851
C_1	-26.3254	0.0781	-25.4551	0.1204
S_1	-8.3304	0.0781	-7.6758	0.1204
C_2	-1.4249	0.0781	-1.2151	0.1204
S_2	-0.5198	0.0781	-0.6731	0.1204
C_3	-0.5433	0.0781	-0.5060	0.1204
S_3	-1.2559	0.0781	-1.0473	0.1204
C_4	0.1131	0.0781		
S_4	-0.2720	0.0781		
C_5	0.0743	0.0781		
S_5	0.3328	0.0781		
C_6	0.4958	0.0781		
S_6	-0.0171	0.0781		

[a] See Equation (3.6) for coefficient definitions.
[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.6. Fourier series coefficient estimates for the mean of the minimum air temperature on a wet day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	33.5774	0.1367	38.3504	0.1548
C_1	-27.1519	0.1934	-25.0132	0.2189
S_1	-8.7806	0.1934	-8.0771	0.2189
C_2	-3.0643	0.1934	-2.3501	0.2189
S_2	-1.2747	0.1934	-1.2593	0.2189
C_3	-0.7844	0.1934	-0.9538	0.2189
S_3	-1.2311	0.1934	-0.9808	0.2189

[a] See Equation (3.6) for coefficient definitions.
[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.7. Fourier series coefficient estimates for the standard deviation of the maximum air temperature on a dry day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	11.1102	0.0395	10.0688	0.0670
C_1	2.8808	0.0559	2.9809	0.0947
S_1	1.2214	0.0559	1.3168	0.0947
C_2	-0.5267	0.0559	-0.6754	0.0947
S_2	-0.2341	0.0559	-0.1711	0.0947
C_3	0.1342	0.0559		
S_3	0.2585	0.0559		
C_4	0.2079	0.0559		
S_4	0.3425	0.0559		
C_5	-0.1920	0.0559		
S_5	0.2608	0.0559		
C_6	-0.2079	0.0559		
S_6	0.0854	0.0559		
C_7	-0.0636	0.0559		
S_7	-0.2245	0.0559		
C_8	-0.0874	0.0559		
S_8	-0.2487	0.0559		

[a] See Equation (3.6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.8. Fourier series coefficient estimates for the standard deviation of the maximum air temperature on a wet day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	10.2603	0.0944	9.8459	0.1166
C_1	1.8704	0.1335	2.0811	0.1649
S_1	0.8781	0.1335	1.2429	0.1649
C_2	-0.6026	0.1335	-0.9649	0.1649
S_2	-0.5283	0.1335	-0.6009	0.1649
C_3	0.5335	0.1335		
S_3	0.4154	0.1335		

[a] See Equation (3.6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.9. Fourier series coefficient estimates for the standard deviation of the minimum air temperature on a dry day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	10.4959	0.0400	9.5900	0.0616
C_1	3.0695	0.0566	2.8803	0.0872
S_1	0.9792	0.0566	0.8108	0.0872
C_2	0.7013	0.0566	0.5321	0.0872
S_2	1.0220	0.0566	0.4681	0.0872
C_3	0.2662	0.0566	0.3502	0.0872
S_3	0.8091	0.0566	0.7953	0.0872
C_4	-0.1969	0.0566		
S_4	-0.2837	0.0566		
C_5	-0.1496	0.0566		
S_5	-0.3494	0.0566		

[a] See Equation (3.6) for coefficient definitions.
[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

Table 3.10. Fourier series coefficient estimates for the standard deviation of the minimum air temperature on a wet day for Brookings, SD and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	9.3562	0.0970	8.9704	0.1161
C_1	3.8418	0.1371	4.1114	0.1643
S_1	0.9883	0.1371	0.9426	0.1643
C_2	0.6352	0.1371	0.5169	0.1643
S_2	0.5066	0.1371	0.2418	0.1643
C_3	0.1161	0.1371	0.3764	0.1643
S_3	0.5401	0.1371	0.6857	0.1643
C_4	-0.3181	0.1371		
S_4	-0.3372	0.1371		
C_5	-0.1425	0.1371		
S_5	-0.7686	0.1371		
C_6	0.0023	0.1371		
S_6	-0.4120	0.1371		

[a] See Equation (3.6) for coefficient definitions.
[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives, see Greene (1997) p. 139.

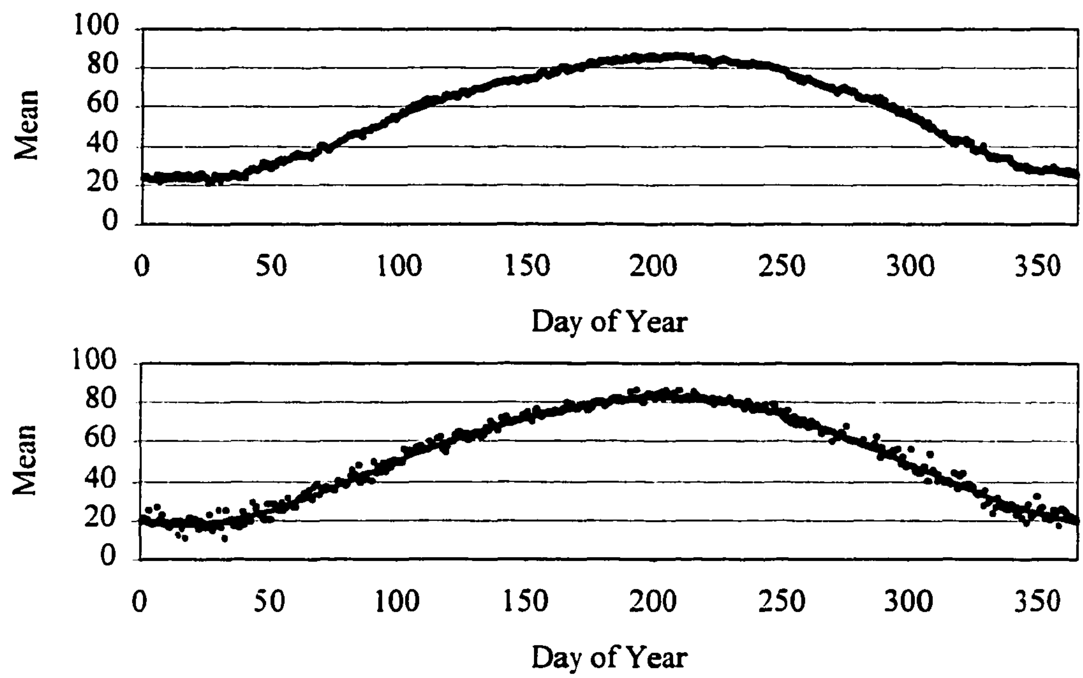


Figure 3.4. Observed and Fourier series estimated daily mean (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD

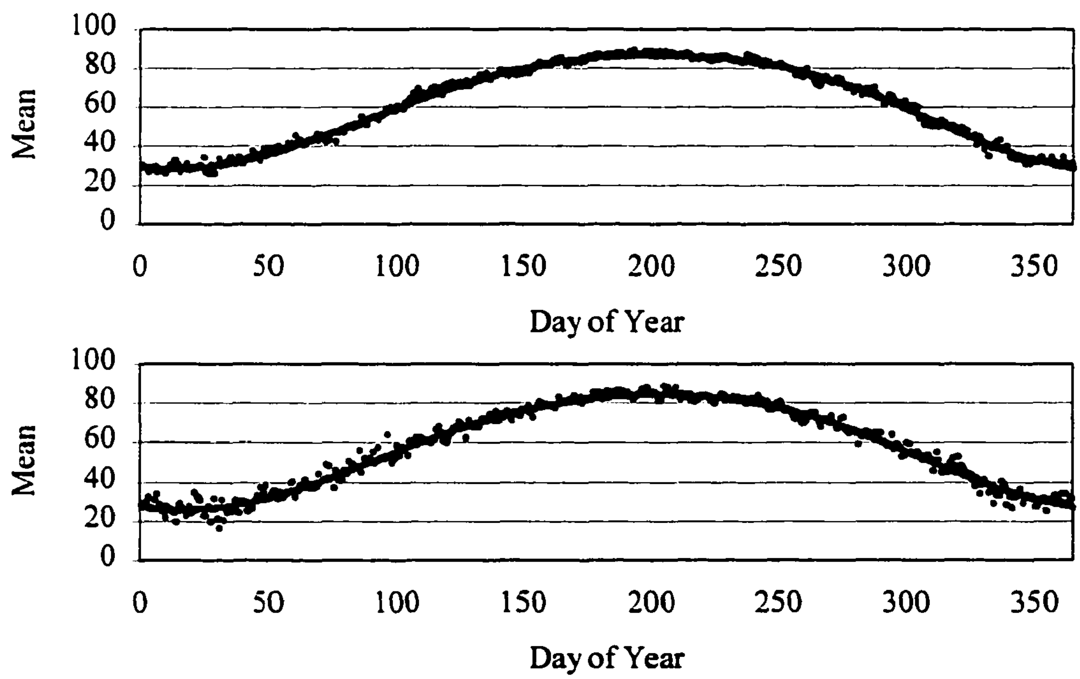


Figure 3.5. Observed and Fourier series estimated daily mean (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA

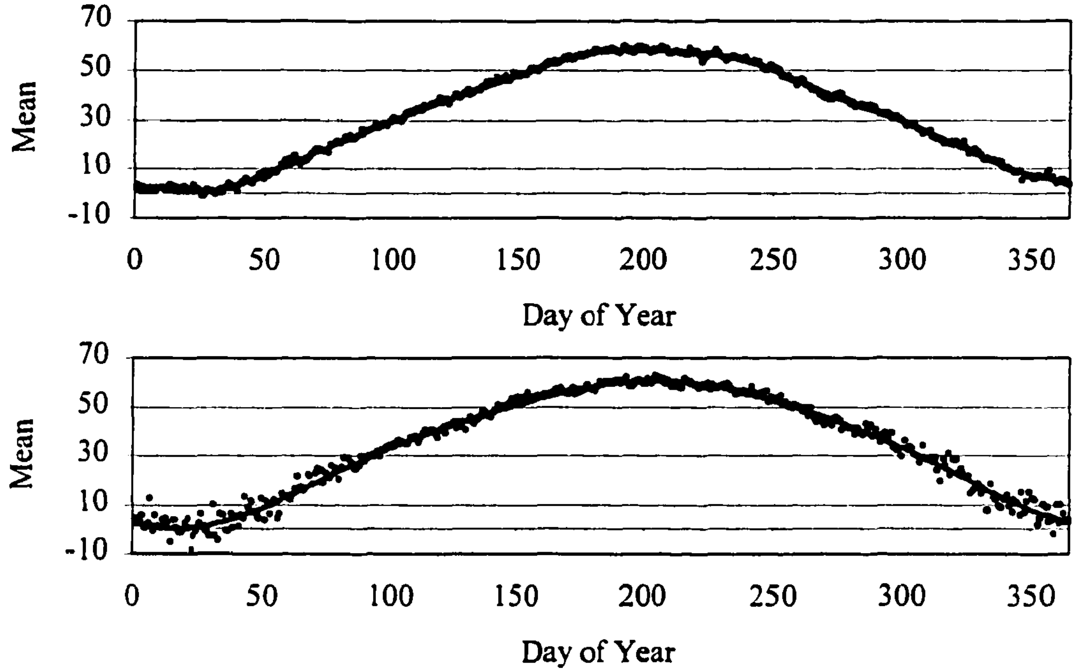


Figure 3.6. Observed and Fourier series estimated daily mean (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD

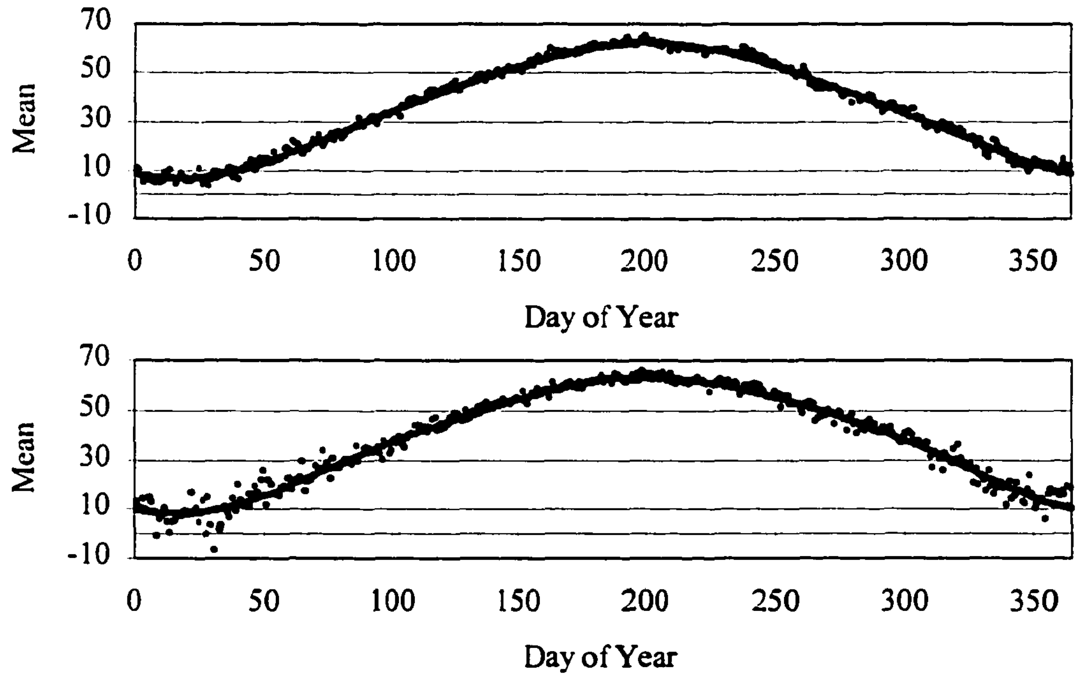


Figure 3.7. Observed and Fourier series estimated daily mean (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA

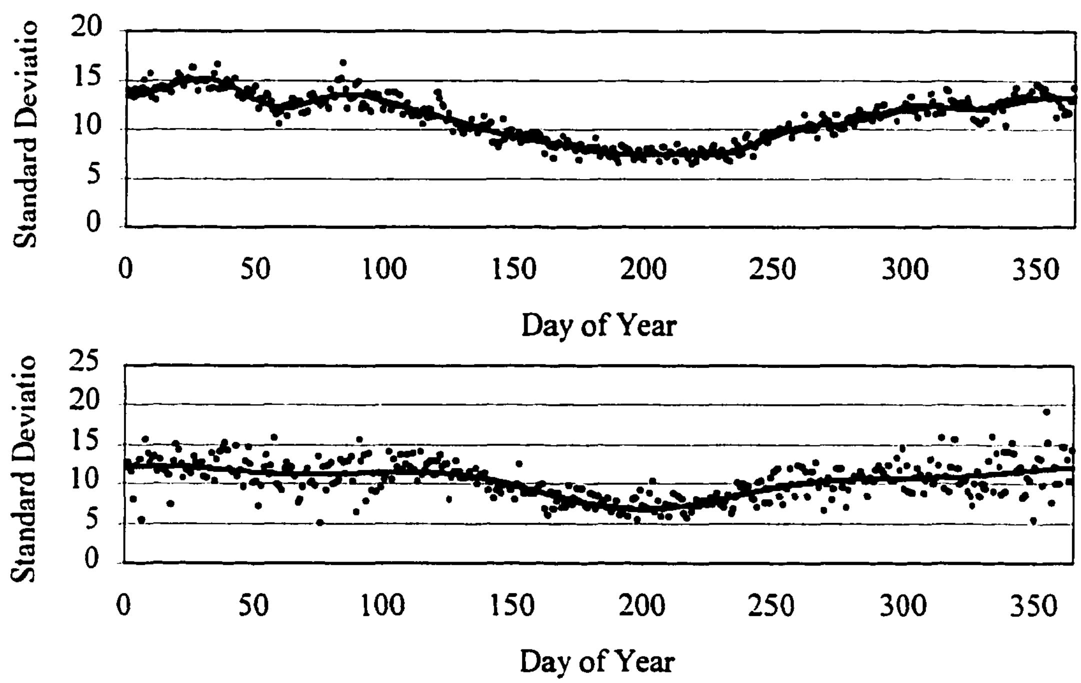


Figure 3.8. Observed and Fourier series estimated daily standard deviation (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD

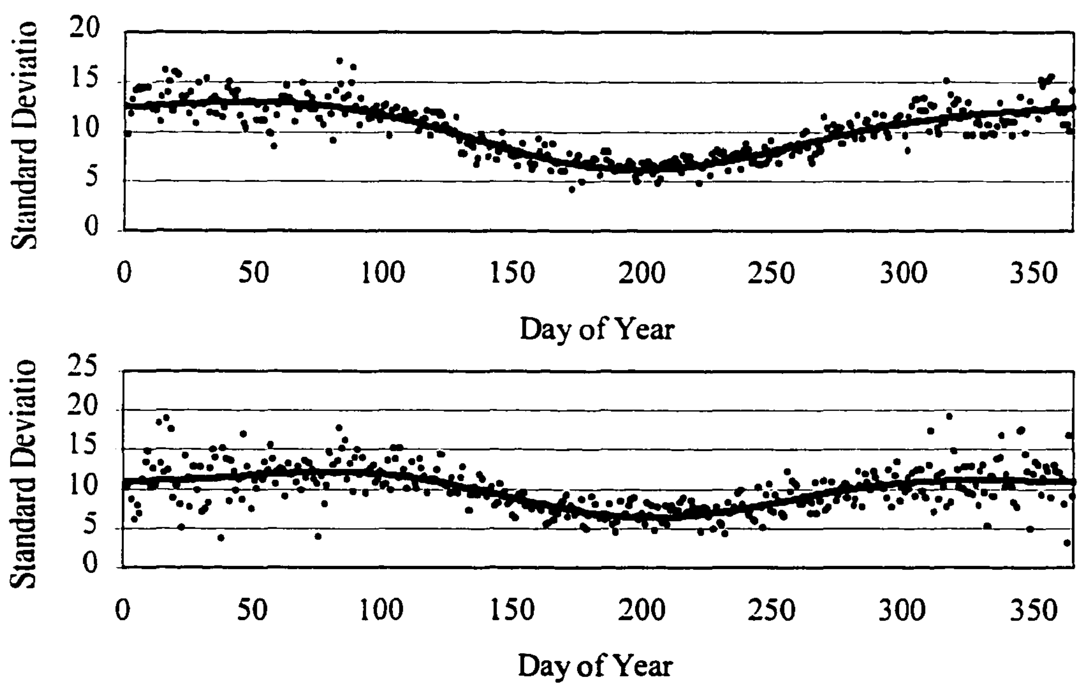


Figure 3.9. Observed and Fourier series estimated daily standard deviation (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA

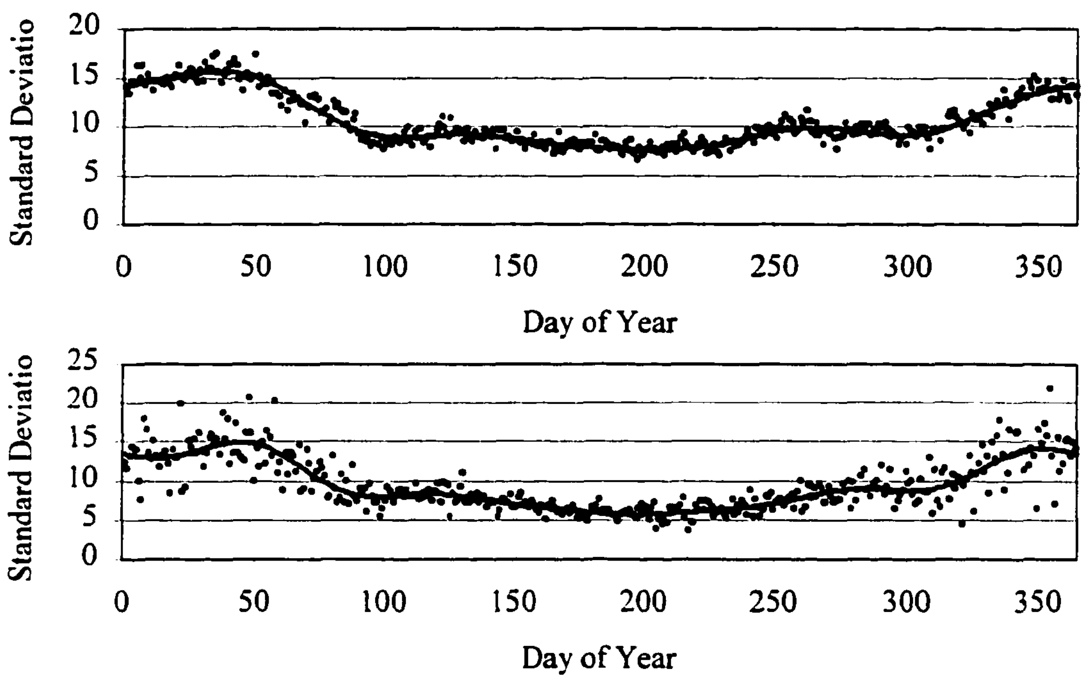


Figure 3.10. Observed and Fourier series estimated daily standard deviation (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD

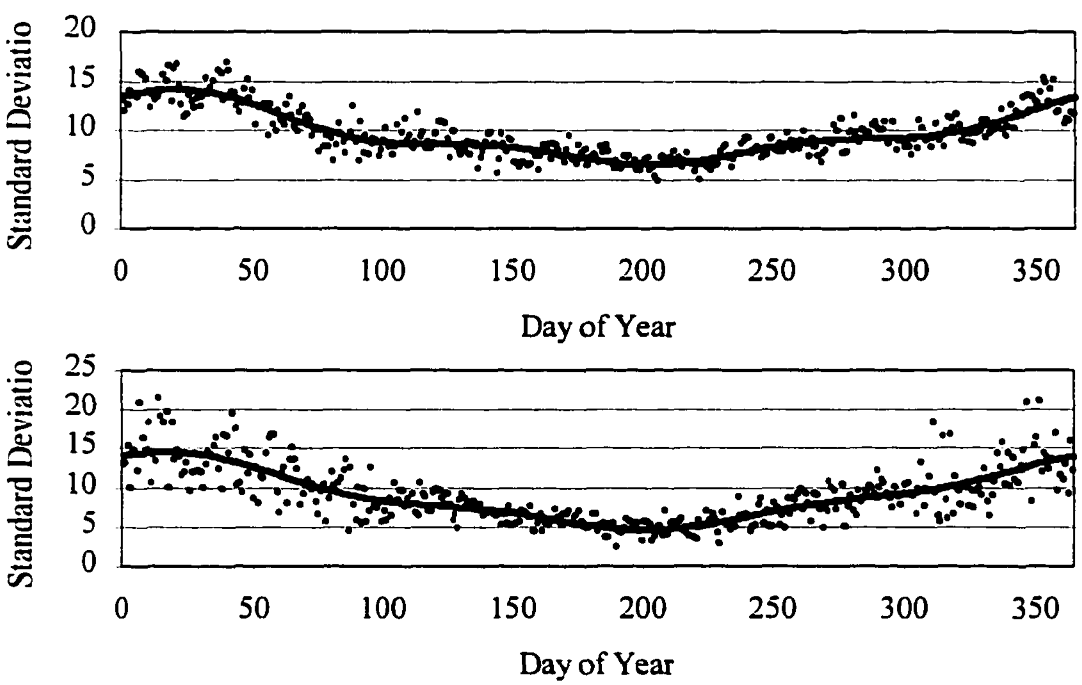


Figure 3.11. Observed and Fourier series estimated daily standard deviation (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA

3.2.4.3 Correlation of Maximum and Minimum Air Temperatures

Following the method described by Matalas (1967), the maximum and minimum air temperatures were assumed to follow a multivariate weakly stationary process defined by:

$$\chi_{n+1,y} = A\chi_{n,y} + B\varepsilon_{n+1,y}, \tag{3.7}$$

where $\chi_{n,y}$ and $\chi_{n+1,y}$ are (2 x 1) matrices for days n and $n + 1$ of year y, whose elements are the residuals for the maximum and minimum air temperatures for the specified day and year, while $\varepsilon_{n,y}$ is a (2 x 1) matrix of independently distributed normal random variables for the specified day and year with a mean of zero and a variance of one. Residuals for the maximum and minimum air temperatures for any day are obtained by removing the mean and standard deviation for that day calculated with data from several years. A and B are (2 x 2) matrices whose elements are defined such that the series of residuals has the desired serial correlation and cross-correlation coefficients. Assuming (3.7) implies that the residuals are also normally distributed and follow a first-order linear autoregressive process. Multiplying each residual by the appropriate daily standard deviation (wet or dry) and adding the appropriate mean (wet or dry) then generates a series of daily maximum and minimum air temperatures.

The elements of A and B are defined as functions of the lag 0 and lag 1 cross-correlation coefficients of the maximum and minimum air temperature residuals at a location. For this application, the series of daily residuals for the maximum and minimum air temperatures are calculated by subtracting the appropriate observed mean (wet or dry) for each day and dividing by the appropriate observed standard deviation for each day. Using these residuals, A and B are determined by the following equations:

$$A = M_1 M_0^{-1} \tag{3.8}$$

$$BB^T = M_0 - M_1 M_0^{-1} M_1^T . \tag{3.9}$$

M_0 and M_1 are matrices of the lag 0 and lag 1 correlation coefficients respectively, defined as follows:

$$M_0 = \begin{bmatrix} 1 & \rho_{X_0 N_0} \\ \rho_{N_0 X_0} & 1 \end{bmatrix} \tag{3.10}$$

$$M_1 = \begin{bmatrix} \rho_{X_0 X_{-1}} & \rho_{X_0 N_{-1}} \\ \rho_{N_0 X_{-1}} & \rho_{N_0 N_{-1}} \end{bmatrix}, \tag{3.11}$$

where X and N denote the residuals for the maximum and minimum air temperature respectively and their subscripts denote lag 0 or lag 1. Thus $\rho_{X_0 N_0}$ is the lag 0 cross correlation coefficient between the residuals for the maximum air temperature and the residuals for the minimum air temperature, $\rho_{X_0 X_{-1}}$ and $\rho_{N_0 N_{-1}}$ are the lag 1 serial correlation for the residuals of the maximum and minimum air temperature respectively, $\rho_{X_0 N_{-1}}$ is the cross correlation coefficient between the lag 0 maximum air temperature residuals and the lag 1 minimum air temperature residuals, while $\rho_{N_0 X_{-1}}$ is the cross correlation coefficient between the lag 0 minimum air temperature residuals and the lag 1 maximum air temperature residuals. Table 3.11 reports the serial correlation and cross correlation coefficients needed to construct the M_0 and M_1 matrices for Brookings, SD and Boone, IA.

To solve (3.9) for B, first define a matrix $Z = BB^T$. Using the spectral decomposition of Z, $Z = C\Lambda C^T$, where C is the matrix of eigenvectors, and Λ is the matrix with the associated eigenvalues down the main diagonal and zeros for all other elements (see Greene

Table 3.11. Correlation coefficients for temperature residuals and derived matrix elements for Brookings, SD and Boone, IA

Coefficient or Element	Value for Brookings, SD	Value for Boone, IA
$\rho_{X_0 N_0} = \rho_{N_0 X_0}$	0.69580	0.69215
$\rho_{X_0 X_{-1}}$	0.67244	0.61300
$\rho_{N_0 N_{-1}}$	0.61889	0.64883
$\rho_{X_0 N_{-1}}$	0.51265	0.51185
$\rho_{N_0 X_{-1}}$	0.59365	0.55112
$A_{1,1}$	0.61206	0.49666
$A_{1,2}$	0.08678	0.16809
$A_{2,1}$	0.31603	0.19587
$A_{2,2}$	0.39900	0.51326
$B_{1,1}$	0.71160	0.75178
$B_{1,2} = B_{2,1}$	0.19382	0.21057
$B_{2,2}$	0.72656	0.71742

(1998) p. 38). Note that $BB^T = Z^{½}Z^{½T} = Z$, implying that $B = Z^{½}$, then by Greene's Theorem 2.10, $B = Z^{½} = C\Lambda^{½}C^T$. Table 3.11 also reports the elements of A and B.

3.2.4.4 Summary of Air Temperature Model

The generation of stochastic daily maximum and minimum air temperatures according to the procedure described in this section requires four steps. First, draw two independent standard normal (mean zero, variance one) random variates for the day. Second, use equation (3.7) to calculate the residuals for the day's maximum and minimum air temperature. Third, use the day's precipitation status (wet or dry) to calculate the mean and standard deviation of the maximum and minimum air temperature using the appropriate Fourier series. Fourth, determine the day's maximum and minimum air temperature by multiplying the appropriate residual by the standard deviation and adding the mean.

3.2.5 Soil Temperature Model

3.2.5.1 Introduction

A method of determining daily soil temperatures was needed, since a significant portion of the corn rootworm life cycle takes place underground. Modeling the temperature of the top 10 cm layer of soil was chosen based on typical depths reported in the literature for corn rootworm activity (Calkins and Kirk 1969, Gustin 1981, Mullock et al. 1995). The method of Potter and Williams (1994) was used with a few modifications to determine the daily average soil temperature as a function of air temperature. The method of Logan et al. (1979) was modified in accordance with data presented in Gupta et al. (1983) to determine the daily maximum and minimum soil temperature as a function of the average soil temperature.

3.2.5.2 Daily Average Soil Temperature Model

The model of Potter and Williams (1994) derives the average soil temperature for a layer below the surface by first modeling the temperature of the bare soil surface, which closely follows the air temperatures, then adjusting this bare soil surface temperature to account for soil cover. Next a physically derived depth-weighting factor is used to determine the average soil temperature at any given depth between the soil surface and the constant temperature depth. Following their model, the potential temperature of the bare soil for day n ($PTBS_n$) depends on a day's precipitation status as follows:

$$PTBS_n = \begin{cases} T_{Min,n} + \dfrac{NWD_n}{30}\alpha_n^{\mathrm{air}} & \text{if the day is wet} \\ T_{Avg,n} + \dfrac{NWD_n}{30}\alpha_n^{\mathrm{air}} & \text{if the day is dry} \end{cases} \tag{3.12}$$

where NWD is the number of wet days over the past thirty days (including the current day), $T_{Max,n}$, $T_{Min,n}$, and $T_{Avg,n}$ are the maximum, minimum and average air temperature for day n (the average temperature is the simple average of the maximum and minimum), and $\alpha_n^{air} = \frac{1}{2}\left(T_{Max,n}^{air} - T_{Min,n}^{air}\right)$ is the amplitude of the temperature change on day n. The actual temperature of the bare soil (TBS_n) is then the two-day-moving average of the $PTBS$.

Next the average soil surface temperature for day n ($T_{Avg,n}^{surface}$) uses the TBS, but accounts for soil cover by using a lagged cover factor (LCF_n) as follows:

$$T_{Avg,n}^{surface} = LCF_n TBS_{n-1} + (1 - LCF_n)TBS_n \qquad (3.13)$$

$$LCF_n = MAX\{BCF_n, SCF_n \qquad (3.14)$$

BCF_n is the biomass cover factor and SCF_n is the snow cover factor for day n calculated by the following empirically derived equations:

$$BCF_n = \frac{B_n}{B_n + \exp(5.3396 - 2.3951 B_n)} \qquad (3.15)$$

$$SCF_n = \frac{S_n}{S_n + \exp(2.303 - 0.2197 S_n)} \qquad (3.16)$$

where B_n is the total above ground crop biomass and surface residue (Mg/ha) and S_n is the water content of the snow cover (mm) on day n. After testing the model, Potter and Williams (1994) impose the following restrictions: $0 \leq BCF_n \leq 0.19$ and $0 \leq SCF_n \leq 0.95$.

To determine B_n, the base cover contributed by crop residue was assumed to be 1.4 Mg/ha, which is approximately the amount of residue left from continuous corn production under conventional tillage. This was determined by assuming a 1:1 ratio of grain to residue production for corn, following Larson et al. (1978, cited in Havlin et al. 1990) and assuming a bushel of corn weighs 56 lbs (USDA 1979). Thus a typical yield for Brookings, SD of 100 bu/ac implies 6.3 Mg/ha of residue and a typical yield for Boone, IA of 150 bu/ac implies 9.4 Mg/ha. Next, standard tillage operations for conventional tillage corn were taken from state extension budgets for South Dakota (chisel plow and tandem disk) and Iowa (chisel plow, tandem disk, and field cultivator) (SDSU Extension Economics 1998, ISU Extension 1998). Residue mixing efficiencies typical for these operations were obtained from the EPIC User's Guide—chisel plow: 0.42, tandem disk: 0.50, field cultivator: 0.70 (Mitchell et al. 1997). Thus 6.3 x 0.42 x 0.50 = 1.32 and 9.4 x 0.42 x 0.50 x 0.70 = 1.38 were rounded up to 1.4 to serve as a simple estimate of the base cover from crop residue.

To include the contribution of growing crop biomass to B_n, the year was divided into four periods roughly coinciding with seasons: (1) no living crop biomass, (2) linear biomass accumulation during crop growth, (3) maintenance of living crop biomass during summer, and (4) linear decline of crop biomass during senescence and harvest. For each of these periods, the value of B_n was determined as follows:

November 1 to plant day $\quad B_n = 1.4 \quad$ (3.17a)

Plant day to peak flower $\quad B_n = 1.4 + 7\left(\dfrac{\text{current day} - \text{plant day}}{\text{peak flower} - \text{plant day}}\right) \quad$ (3.17b)

Peak flower to harvest $\quad B_n = 9.4 \quad$ (3.17c)

Harvest to November 1 $\quad B_n = 9.4 - 7\left(\dfrac{\text{current day} - \text{harvest}}{305 - \text{harvest}}\right) \quad$ (3.17d)

Plant days range from early May to early June, with early to mid-May typical. Peak flower depends on the maturity of the corn hybrid and occurs from early August to mid September, with mid to late August typical. Harvest can range from as early as late September to as late as late November, but mid-October is typical.

To determine S_n, the water content of snow cover (mm), a model of snowfall accumulation and snowmelt was used. If precipitation occurred on a day, it was categorized as snowfall if the maximum air temperature was less than 40° F and the average was below 35° F. The multiple-layer soil temperature model of snowmelt developed by Williams (1995) was adapted to the single-layer soil temperature model used here. If a snow pack is present and the average soil temperature on day n ($T_{Avg,n}^{soil}$) is above zero, then the millimeters of snowmelt on day n (SM_n) occurs according to the empirically derived equation:

$$SM_n = T_{Avg,n}\left(1.52 + 0.54 MIN\left\{T_{Avg,n}^{soil}, T_{Avg,n}\right\}\right). \tag{3.18}$$

The method of Potter and Williams (1994) was then used to determine the daily average soil temperature at 5 cm, the middle of the top 10 cm of soil, as follows:

$$T_{Avg,n}^{soil} = 0.5 T_{Avg,n-1}^{soil} + 0.5 T_{Avg,n}^{surface} + 0.5 DWF\left(\overline{T} - T_{Avg,n}^{surface}\right). \tag{3.19}$$

$\overline{T}$ is the long term average air temperature that approximates the constant soil temperature maintained at some sufficient depth (6.2°C for Brookings and 8.5°C for Boone) and DWF is the depth weighting factor. Potter and Williams (1994) equations (7) – (11) were used to determine the value of DWF over a wide range of soil bulk density and soil water conditions. The value changed very little (0.2237 – 0.2260), even under extraordinarily unlikely conditions, so an average value of 0.225 was used for all simulations. Because the model tended to under predict average soil temperatures (Potter and Williams 1994), the average was increased by 2.5% for all simulations.

3.2.5.3 Daily Maximum and Minimum Soil Temperature Model

To determine the daily maximum and minimum soil temperature, the method of Logan et al. (1979) was modified to extrapolate from air temperature extremes to near-surface soil temperature extremes. Their method was intended to extrapolate from measured temperatures at one depth to temperatures at another depth and not from surface to below-ground temperatures. Essentially, the method assumes that the amplitude at one depth is proportional to the amplitude at another depth, with the constant of proportionality depending on the difference in depth. Using Logan et al.'s equation (9), a value of 0.98 was estimated for a depth difference of 10 cm. Assuming that the soil surface temperature is the same as the air temperature, this factor implies that the amplitude of soil temperatures at 5 cm is 98% of the amplitude of the air temperature. However, this does not account for dampening due to soil cover, nor to additional heat input from solar radiation, especially significant in spring when the soil is dark and crops do not shade the soil surface.

To adjust for soil cover, the constant of proportionality was reduced to 0.95 for days between March 1 and November 15 (approximately soil thaw to soil freeze). Benoit and Van Sickle (1991) report data on winter soil temperatures for various tillage-residue management systems in west central Minnesota. These data indicate that the difference between the maximum and minimum air temperatures was around 10-12°C, while the difference between the maximum and minimum soil temperatures at 5 cm was about 2-4°C, or about 25% less. Thus from November 15 to March 1, the constant of proportionality was set to 0.25.

Research has also shown that the variation of near-surface soil temperatures around the average is asymmetric and changes throughout the season due to tillage and crop growth (Gupta et al. 1981, Gupta et al. 1983, Potter and Williams 1994). Data reported by Gupta et al. (1983) indicate that in spring the maximum soil temperature is approximately 25% more above the average soil temperature than the maximum air temperature is above the average air temperature. This occurs since the soil is generally dark and no crops provide shade. In summer the factor is approximately 15%, since solar radiation has increased, but crops begin to provide increasingly more shade.

All these adjustments are summarized in the equations used to determine the soil maximum and minimum temperatures:

Spring (March 1 to plant day + 42 days):

$$T^{soil}_{Max,n} = 1.25\left[T^{soil}_{Avg,n} + 0.95\alpha^{air}_{n}\right] \tag{3.20a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.95\alpha^{air}_{n}\right] \tag{3.20b}$$

Summer (plant day + 42 days to September 15):

$$T^{soil}_{Max,n} = 1.15\left[T^{soil}_{Avg,n} + 0.95\alpha^{air}_{n}\right] \tag{3.21a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.95\alpha^{air}_{n}\right] \tag{3.21b}$$

Fall (September 15 to November 15):

$$T^{soil}_{Max,n} = 1.00\left[T^{soil}_{Avg,n} + 0.95\alpha^{air}_{n}\right] \tag{3.22a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.95\alpha^{air}_{n}\right] \tag{3.22b}$$

Winter (November 15 to March 1):

$$T^{soil}_{Max,n} = 1.00\left[T^{soil}_{Avg,n} + 0.25\alpha^{air}_{n}\right] \tag{3.23a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.25\alpha^{air}_{n}\right] \tag{3.23b}$$

3.2.5.4 Summary of Soil Temperature Model

The overall performance of the soil temperature model was difficult to evaluate, since no actual soil temperature data were available. However, it is based on modeling assumptions and equations well-tested in the literature, e.g. Potter and Williams (1994) is the soil temperature model used for EPIC. The soil temperature model developed here predicts the daily average, maximum, and minimum soil temperature as a function of the daily maximum and minimum air temperature and precipitation status (wet or dry). Furthermore, it accounts for the impact of crop growth and seasonal changes, including snowfall accumulation.

3.2.6 Algorithm for Calculating Degree Days

Many corn rootworm population models require heating and/or cooling degree-days for air and/or soil temperatures (e.g. Hein and Tollefson 1987, Naranjo and Sawyer 1989a, Schaafsma et al. 1991, Davis et al. 1996). As a result, it seems appropriate to report the algorithm used to calculate heating and cooling degree days, since several alternative methods are available. Higley et al. (1986) compare three methods and recommend the sine wave method proposed by Arnold (1960), with the modifications and algorithm developed by Allen (1976).

In essence, all degree day algorithms use simplifying assumptions to estimate the area under the time series of observed temperatures. Allen's (1976) algorithm calculates degree days by half days, assuming twelve hours between the previous day's maximum, the current day's minimum, and the current day's maximum. The temperature time series is approximated as a sine wave between the two observed times, then the area under this time series, after accounting for upper and/or lower temperature thresholds, is the degree days for the half day.

For the model here, only a lower temperature threshold was utilized; this threshold is often referred to as the base temperature (T_{Base}) in the literature. Only three relationships between the observed temperatures and the base are possible: (1) observed maximum and minimum below the base, (2) observed maximum and minimum above the base, and (3) observed minimum below the base and observed maximum above the base. For the first two cases, determination of heating degree days (HDD) and cooling degree days (CDD) for a half day is rather simple. Calculating the area of a simple rectangle yields the same area as the sine function, since the sine function is symmetric. Half of the rectangle's area is the degree day accumulation occurring during the half day, hence the 0.5 factor in equations (3.24b) and (3.25a). The formulas for half days are:

Case 1: $$HDD = 0.0 \tag{3.24a}$$

$$CDD = 0.5\left(T_{Base} - T_{Avg}\right) \tag{3.24b}$$

Case 2: $$HDD = 0.5\left(T_{Avg} - T_{Base}\right) \tag{3.25a}$$

$$CDD = 0.0 \tag{3.25b}$$

For the third case, the calculations are more complex since the base temperature threshold is crossed. Defining $\alpha = \frac{1}{2}\left(T_{Max} - T_{Min}\right)$ as the amplitude of the temperature change and θ as the estimated time (in radians) when the temperature crosses the base temperature threshold:

$$\theta = \tan^{-1}\left[\frac{\frac{1}{\alpha}\left(T_{Base} - T_{Avg}\right)}{\sqrt{1 - \left[\frac{1}{\alpha}\left(T_{Base} - T_{Avg}\right)\right]^2}}\right] \tag{3.26a}$$

$$HDD = \frac{1}{2\pi}\left[\left(T_{Avg} - T_{Base}\right)\left(\frac{\pi}{2} - \theta\right) + \alpha\cos(\theta)\right] \tag{3.26b}$$

$$CDD = \frac{1}{2\pi}\left[\left(T_{Base} - T_{Avg}\right)\left(\theta + \frac{\pi}{2}\right) + \alpha\cos(\theta)\right] \tag{3.26c}$$

To accommodate an hourly time step simply requires changing the $\frac{1}{2}$ to $\frac{1}{24}$ in equations (3.24b) and (3.25a) and the $\frac{1}{2\pi}$ to $\frac{1}{24\pi}$ in equations (3.26b) and (3.26c).

3.3 Corn Rootworm Population Model

3.3.1 Introduction

The corn rootworm population model developed here primarily uses the model of Naranjo and Sawyer (1989a, 1989b), but with some modifications and extensions necessary to fulfill the needs of this study. This section presents the details of the population model as used, so the study can be replicated, and explains and justifies any differences between this model and the original model of Naranjo and Sawyer. The interested reader should consult the original papers of Naranjo and Sawyer to obtain a more thorough discuss of the assumptions and justification of the original model.

The model of Naranjo and Sawyer was developed from both laboratory and field data and documented in several papers (Naranjo and Sawyer 1987, 1988a, 1988b, 1989a, 1989b). It is a multiple-cohort age-structured process model of the single season adult population dynamics and oviposition of northern corn rootworm, with stochastic development and advancement. A cohort is the group of individuals who entered a given life stage during the same time period, e.g. all the adults who emerged from their pupal cells during the same half-day. The model maintains several cohorts for each life stage and, since the individuals in the same cohort are all of the same age and this age is explicitly modeled, the model is a multiple-cohort age-structured model. Individual development within a life stage and advancement to the next stage is stochastic, with the probability of advancement conditional on age. To extend the model to cover the full life cycle and full season required a model of egg hatch and larval and pupal survival to adult emergence. These models were developed primarily from the work of Woodson and Ellsbury (1994) and Riedell et al. (1996).

What follows in the rest of this section is first a description of the modified form of Naranjo and Sawyer's model of adult emergence and oviposition, then a description of the hatch and larval survival model used to complete the life cycle model.

3.3.2 Model of Adult Population Dynamics and Oviposition

3.3.2.1 Introduction

The original model of Naranjo and Sawyer includes seven stages of the corn rootworm life cycle: (1) male pupae, (2) female pupae, (3) adult males, (4) immature adult females, (5) mature adult females, (6) post-reproductive adult females, and (7) eggs. Populations in the first two stages are not modeled, but obtained from field data, or in the case of the model used here, from the model of larval survival described in the next sub-section. The development and hatch of the last stage, eggs, is not modeled either, but serves as input into the egg hatch model described in the next sub-section as well.

The original model of Naranjo and Sawyer is presented with continuous time equations, but when actually implemented, a discrete time step of one day is used. The model presented here is presented in the discrete form as implemented and a half day time step is used. The half day time step explicitly accounts for the fact that the maximum and minimum temperatures for a day do not occur at the same time. For any given day of the year, the first half day occurs from the previous day's maximum to the current day's minimum, while the second half day occurs from the current day's minimum to the current day's maximum. Following Naranjo and Sawyer (1989a), the first half day lasts 15 hours (2 PM to 5 AM for air, 4 PM to 7 AM for soil) and the second half day lasts 9 hours (5 AM to 2 PM for air, 7 AM to 4 PM for soil).

The corn rootworm population has experienced strong evolutionary selection pressure to coordinate their life cycle with the development of their host plant. As a result, corn phenology exerts an important influence on adult population dynamics and oviposition. In the model of Narnajo and Sawyer, this influence is incorporated by the use of the planting date and day of peak corn flowering in several equations. The day of peak flower is determined by the variety of corn planted (the "day" value of the variety) and the weather.

3.3.2.2 Equations for Adult Population Dynamics

For the four adult stages, the population of each cohort and advancement into the next stage is described by the following system of equations:

$$P_{c,t}^{ImmF} = \begin{cases} E_t^{ImmF} & \text{if } c = 1 \\ P_{c,t-1}^{ImmF}\left(1 - k_t M_t\right)\left(1 - k_t A_{c,t}^{ImmF}\right) & \text{if } c > 1 \end{cases} \tag{3.27}$$

$$P_{c,t}^{MatF} = \begin{cases} \sum_{c=1}^{C_t^{ImmF}} \left[P_{c,t}^{ImmF}\left(1 - k_t M_t\right)\left(k_t A_{c,t}^{ImmF}\right)\right] & \text{if } c = 1 \\ P_{c,t-1}^{MatF}\left(1 - k_t M_t\right)\left(1 - k_t A_{c,t}^{MatF}\right) & \text{if } c > 1 \end{cases} \tag{3.28}$$

$$P_{c,t}^{Post} = \begin{cases} \sum_{c=1}^{C_t^{MatF}} \left[P_{c,t}^{MatF} (1 - k_t M_t)(k_t A_{c,t}^{MatF}) \right] & \text{if } c = 1 \\ P_{c,t-1}^{Post} (1 - k_t M_t) & \text{if } c > 1 \end{cases} \tag{3.29}$$

$$P_{c,t}^{Male} = \begin{cases} E_t^{Male} & \text{if } c = 1 \\ P_{c,t-1}^{Male} (1 - k_t M_t) & \text{if } c > 1 \end{cases} \tag{3.30}$$

$P_{c,t}^{s}$ is the population per square meter of adults in life stage s, in cohort c, during time period t. Life stage $s \in \{ImmF, MatF, Post, Male\}$, for immature female, mature female, post-reproductive female, and male respectively. Cohorts range in number between 1 and C_t^s for each stage, with the number C_t^s varying depending on the time period. When a new cohort advances to the next stage, it starts as cohort $c = 1$, and all existing cohorts have their index c incremented by one. The time period $t \in \{n1, n2\}$, where n is the day of the year and $n1$ denotes the first half day for day n, while $n2$ denotes the second half day for day n. Lastly, k_t is the time period conversion factor that converts variables that are in units of days to half days. For $t = n1$, $k_t = 15/24$, since the first half day is 15 hours long, and for $t = n2$, $k_t = 9/24$, since the second half day is 9 hours long.

In equations (3.27) and (3.30), E_t^s is the number of adults of stage s emerging from pupal cells during time step t, and these individuals are the new first cohort for the specified stage. The summations in the first parts of equations (3.28) and (3.29) serve the same purpose—to determine the number of adults advancing to the next stage and becoming the new first cohort. Lastly, M_t is the daily proportional mortality rate and $A_{c,t}^{s}$ is the probability of that members of cohort c will advance during time period t. The equations for determining adult emergence, mortality and advancement probabilities are presented in the next sub-sections.

3.3.2.3 Adult Emergence

The emergence of adults from the soil depends on temperature, day of corn planting, and day of corn peak flowering. Naranjo and Sawyer estimated separate equations for male and female emergence from field data for log-normal density functions of the general form:

$$E_t^s(g_t) = \frac{E_{Total}^s}{g_t \sigma_E^s \sqrt{2\pi}} \exp\left[-\frac{\left(\ln(g_t) - \mu_E^s\right)^2}{2\sigma_E^{s\,2}} \right] (g_t - g_{t-1}). \tag{3.31}$$

E_{Total}^s is the total number of males (s = *Male*) or females (s = *ImmF*) emerging and is determined from E_{Total}, the total number of males and females emerging. E_{Total} is obtained from the model of larval survival, and the proportion of E_{Total} that is female (ψ) depends on the plant day and day of peak flower according to the following equation:

$$= -0.15 + 0.00080x, \tag{3.32}$$

where x is the sum of soil degree days with a base of 10°C from March 1 to the plant date and air degree days with a base 10°C from the plant date to the day of peak flower. The value of ψ was truncated at 0.85 to ensure that no more than 85% of the emerging adults were female.

In equation (3.31), g_t is time measured in accumulated soil degree days with a base of 10°C from March 1, and μ_E^s and σ_E^s are the mean and standard deviation of emergence times on a natural logarithm scale for the specified stages. Mean emergence times depend on the planting date and day of peak flower according to the following equations:

$$\exp\left(\mu_E^{Male}\right) = 547.88 + 0.39x \tag{3.33a}$$

$$\exp\left(\mu_E^{ImmF}\right) = 800.85 + 0.24x \tag{3.33a}$$

where x is as defined for equation (3.32). Lastly, $\sigma_E^{Male} = 0.0901$ and $\sigma_E^{ImmF} = 0.0998$.

3.3.2.4 Mortality

The daily proportional rate of mortality depends on the proportion of corn plants in flower (ψ_{flwr}) according to the following equation:

$$M_t(\psi_{flwr}) = M_{Max} \exp\left(-\phi\, \psi_{flwr}\right) \tag{3.34}$$

where M_{Max} is the maximum proportional rate of mortality and ϕ determines the rate of decline in mortality as the proportion of corn plants in flower increases. For the model as implemented here, M_{Max} was set to 0.0715 and ϕ to 1.924. This value for M_{Max} is approximately a 50% reduction from the value used by Naranjo and Sawyer (0.143) and was used to correct for prediction biases in the model estimates of population density noted by Naranjo and Sawyer.

The model for corn phenology uses a probability density function for plant development that depends on physiological time as measured by d, the air degree days for a base of 10°C accumulated from the plant date. Naranjo and Sawyer use a logistic density function and ψ_{flwr} is determined by integrating between the limits $c1$ and $c2$ as follows:

$${}_{flwr} = \frac{1}{1+\exp\left(-\frac{c2-d}{\sqrt{d}}\right)} - \frac{1}{1+\exp\left(-\frac{c1-d}{\sqrt{d}}\right)} \tag{3.35}$$

Values for $c1$ and $c2$ depend on temperature as well, and are determined as follows:

$$c1 = -2.57 + 0.86y \tag{3.36a}$$

$$c2 = 127.51 + 0.97y, \tag{3.36b}$$

where y is the air degree days for a base of 10°C accumulated from planting date to the day of peak flower.

3.3.2.5 Age-Dependent Probability of Advancement

Immature and mature females develop at rates that depend on air temperatures and residence time within a stage varies considerably among individuals. A multiple-cohort age-dependent stochastic model of female development was constructed by linking an age-dependent distribution model for stage residence time with a temperature-dependent model for rates of development within a stage. To reiterate, a cohort is defined as a group of individuals who entered a given stage at the same time. In the model as implemented, two variables define a cohort and must be updated for each time step: the number of individuals in the cohort ($P^s_{c,t}$) and their physiological age ($a^s_{c,t}$), where c denotes the cohort number, t the time period and s the stage identifier. Equations (3.27) – (3.30) determine the number of individuals in a cohort, while the equations governing the physiological aging process and the age-dependent probability of advancement remain to be defined.

In equations (3.28) and (3.29), $A^s_{c,t}$ is the probability that individuals in cohort c and stage s will advance to the next stage during time period t. This probability depends on the physiological age of the individuals in the cohort as follows:

$$A^s_{c,t}(a^s_{c,t}) = \frac{F^s(a^s_{c,t}) - F^s(a^s_{c,t-1})}{1 - F^s(a^s_{c,t-1})}, \tag{3.37}$$

where $F^s(a)$ is the distribution function of stage s evaluated at age a. To determine $F^s(a)$, define $z = (V - a)/(V - U)$, then:

$$F(a) = \begin{cases} 0 & \text{if a} < \text{U} \\ (1-z)^{\theta z^{q}} & \text{if U} < \text{a} < \text{V} \\ 1 & \text{if a} > \text{V} \end{cases} \tag{3.38}$$

where the parameters U, V, θ, and q depend on stage $s \in \{ImmF, MatF\}$ as follows: $U^{ImmF} = 0.4710$, $U^{MatF} = 0.0999$, $V^{ImmF} = 2.0300$, $V^{MatF} = 2.8917$, $\theta^{ImmF} = 1.0263$, $\theta^{MatF} = 1.2483$, $q^{ImmF} = 1.1706$, and $q^{MatF} = 0.5471$.

The physiological age of the females in a cohort is determined by integrating the development rate function of the stage from the time individuals enter a stage. This development rate function depends on the temperature (T) and stage-specific parameters. For immature females, $r(T)$ it is determined by the following equation:

$$r(T) = \frac{T(R/298.15)\exp[(HA/1.987)((1/298.15)-(1/T))]}{1+\exp[(HH/1.987)((1/TH)-(1/T))]} \tag{3.39a}$$

where T is temperature in Kelvin, $R = 0.1081$, $HA = 13158.39$, $HH = 58016.57$, and $TH = 302.85$. For mature females, $r(T)$ is determined as follows:

$$r(T) = T(R/298.15)\exp[(HA/1.987)((1/298.15)-(1/T))] \tag{3.39b}$$

where again T is temperature in Kelvin, $R = 0.0358$, and $HA = 10988.04$.

Following Naranjo and Sawyer, a sine function was used to interpolate hourly temperatures between maximum and minimum temperatures, again assuming that the maximum air temperature occurred at 2 PM and the minimum air temperature occurred at 5 AM, and two hours later for soil temperatures for both cases. Denoting the amplitude as $\alpha = \frac{1}{2}(T_{Max} - T_{Min})$ and the period as $p = 2(h_{End} - h_{Begin})$, where h_j is the indicated hour of the day, the temperature (T) at any hour h is:

$$T(h) = T_{Avg} + \alpha \sin\left(\frac{2\pi}{p}\left(h - h_{Begin} + k_{ni} p\right)\right) \tag{3.40}$$

where k_{ni} is a constant depending on which half-day h is in. For the first half day, $k_{n1} = 0.75$ and for the second half day, $k_{n2} = 0.25$.

Using this hourly time step, a simple summation technique was used to approximate the integral of the rate function $r(T)$. Denote and calculate the average development rate for any two subsequent hours h_j and h_{j+1} as follows:

$$r_{Avg}(h_j) = \frac{1}{2}\left(r(T(h_j)) + r(T(h_{j+1}))\right) \tag{3.41}$$

Then the aging that occurs during any half-day time period t is:

$$ag_t = \frac{1}{24} \sum_{h_j = h_{Begin}}^{h_{End}} r_{Avg}(h_j) \tag{3.42}$$

where h_{Begin} = 14 and 5 for $n1$ and $n2$ respectively, and h_{End} = 29 and 14 for $n1$ and $n2$ respectively. Then the age of any cohort c of stage s during any time period t is the sum of all the ag_t that have occurred from the time period when the cohort was created (t_{Begin}) until the current time period $t \geq t_{Begin}$:

$$a^s_{c,t} = \sum_{\tau = t_{Begin}}^{t} ag_\tau \tag{3.43}$$

where the ag_t are those appropriate for the stage (immature or mature females).

3.3.2.6 Oviposition

Only mature females lay eggs. Mating is not modeled, but immature females are assumed to mate soon after emergence and the maturation process is essentially a period during which the fertilized eggs develop within the female until she is ready for oviposition. The daily rate of oviposition per female is an age-dependent function modeled in a manner similar to the advancement and rate of development. Using notation as in (3.27) – (3.30), the total number of eggs oviposited by mature females in cohort c in time period t is:

$$P_{c,t}^{Eggs} = \begin{cases} \sum_{c=1}^{C_t^{MatF}} \left[O(a_{c,t}^{MatF}) P_{c,t}^{MatF} \right] & \text{if } c = 1 \\ P_{c,t-1}^{MatF} + \sum_{c=1}^{C_t^{MatF}} \left[O(a_{c,t}^{MatF}) P_{c,t}^{MatF} \right] & \text{if } c > 1 \end{cases} \tag{3.44}$$

where $O(a)$ is the age-dependent oviposition function. The total number of eggs oviposited by all mature females during the entire season is then the sum of the new oviposition occurring during each time period for all mature female cohorts existing during that time period:

$$P_{Total}^{Eggs} = \sum_{t=1}^{365} \sum_{c=1}^{C_t^{MatF}} O(a_{c,t}^{MatF}) P_{c,t}^{MatF} \tag{3.45}$$

The age-dependent oviposition function $O(a)$ is a combination of a temperature dependent rate function and an age-dependent normal density function:

$$O(a_t, T) = \frac{f(T)}{\sigma_O^s \sqrt{2\pi}} \exp\left[-\frac{(a_t - \mu_O^s)^2}{2\sigma_O^{s\,2}} \right] (a_t - a_{t-1}) \tag{3.46}$$

where a_t is the age of the mature female cohort, and $\mu_O = 1.1222$ and $\sigma_O = 0.6996$ are the mean and standard deviation of the normal density function.

The temperature-dependent fecundity function $f(T)$ has exactly the same form as equation (4.40a), the development rate function for immature females, except the parameters have different values: $R = 776.55$, $HA = 12249.96$, $HH = 64747.54$, and $TH = 300.52$. Fecundity was increased by 50% to correct for the consistent underestimation that Naranjo and Sawyer (1989a) noted occurred with their model.

3.3.2.7 Conclusion

The equations and parameter values given in this section are those used for the model of adult population dynamics and oviposition. The original model of Naranjo and Sawyer included equations governing dispersal. However, the parameters for these equations were estimated as the residuals needed to balance observed data with predictions, and as a result were extremely site- and time-specific. For this reason, the current model does not include a dispersal component.

Naranjo and Sawyer have evaluated their model and conclude that their model provides "a reasonable facsimile of actual system behavior," but is not without its weaknesses. Consistent biases and other problems have been noted, and some parameter values were modified as an attempt to correct for these. Date requirements to implement the model are (1) air and soil temperatures, (2) total number of pupae surviving to emerge as adults, and (3) plant day and day of peak corn flowering. These data are supplied by linking this model with the model of egg hatch and larval survival discussed in the next section and with the stochastic weather generation method discussed in the previous section.

3.3.3 Model of Egg Hatch and Larval Survival

3.3.3.1 Introduction

Woodson et al. (1996) present a multiple cohort model of northern corn rootworm egg development and hatch, but it does not include mortality. In addition, a multiple cohort model similar to the model of Naranjo and Sawyer for the adult stages was not available for the larval and pupal stages. As a result, the work of Woodson et al. (1996) and Woodson and Ellsbury (1994) was used to develop a model of the percent egg hatch, while data from the work of Riedell et al. (1996) was used to develop a density dependent model for the percent larval survival.

3.3.3.2 Model of Egg Hatch

The model of egg hatch predicts the percent of the eggs that survive the winter and hatch the next spring to become the initial larval population for the year. The model used here uses the model of Woodson et al. (1996) to predict the day of median egg hatch and the model of Woodson and Ellsbury (1994) to predict the percent hatch.

Woodson et al. (1996) developed a multiple cohort model of northern corn rootworm egg hatch with stochastic development and advancement analogous to the model of Naranjo and Sawyer for the adult stages, but without mortality. Similar to equations (4.40a) and (4.40b), Woodson et al. estimated the parameters for the following development rate function $r(T)$ for eggs:

$$r(T) = \exp(RT) - \exp\left(RT^{*} - \frac{T^{*} - T}{\delta}\right) + \lambda \tag{3.47}$$

where T is the temperature °C, $R = 0.0050$, $T^{*} = 43.3574$, $\delta = 3.6020$, and $\lambda = -1.0609$. As with adult aging, (3.40) was used to interpolate hourly soil temperatures and the integral of $r(T)$ was approximated by the simple summation technique of (3.41) – (3.43). This integral is the developmental age of the eggs and was accumulated from March 15. The time of median egg hatch occurs when the developmental age equals one. The day of median egg hatch predicted by this model was used for determining the percent egg hatch using a modified form of the model of Woodson and Ellsbury (1994). After running 30 years of simulations, the range of the day of median egg hatch for Brookings, SD was May 15 to June 14 and May 9 to June 4 for Boone, IA. The average Julian day of the median egg hatch was

152.6 (June 1-2) for Brookings, SD and 140.5 (May 20-21) for Boone, IA. These dates agree with field observations (Edwards et al. 1999).

Woodson and Ellsbury collected feral northern corn rootworm eggs from fields around Brookings, SD, then subjected these eggs to various temperature and duration treatments and recorded the percent hatch. From these data, they developed the following model for the percent hatch:

$$H = 42.70 - 5.51T + 5.67D - 0.54T^2 - 0.26D^2 + 0.42TD \tag{3.48}$$

H is the percent hatch, T is the constant temperature °C to which the eggs were exposed, and D is the duration of this exposure in weeks.

The constant temperature model of Woodson and Ellsbury was not suited to predicting percent hatch for eggs exposed to varying temperatures, such as eggs endure in the field. To solve this problem, a new model was developed from their model that determined the percent hatch for eggs exposed to field conditions.

The new model determines the percent hatch as follows:

$$H = B_0 - B_1CDD_{10} + B_2CDD_{10}^2 - B_3STD_{10}. \tag{3.49}$$

CDD_{10} and CDD_{10}^2 are the cooling degree days for a base of 10 °C accumulated from November 15 to the day of median egg hatch and its square respectively. STD_{10} is the number of days that the soil temperature is below 10 °C during the 210 days previous to the day of median egg hatch. Lastly, the B_i are the parameters to estimate. Values for the independent variables could be determined from the temperature and duration treatments reported by Woodson and Ellsbury, as well as from the soil temperature model. To estimate the parameters of the model, for each temperature treatment (0, –2.5, –5, –7.5, –10 °C) and duration treatment (2, 4, 6, 8, 10, 12, 16 weeks), the percent hatch predicted by the Woodson and Ellsbury model was calculated for use as observations of the dependent variable. The cooling degree days for each treatment and its square, as well as the duration in days, were then used as the independent variables for an ordinary least squares regression conducted in Microsoft Excel 97. Coefficient estimates and standard errors are reported in Table 3.12.

Table 3.12. Ordinary least squares coefficient estimates and standard errors for the new model of the percent egg hatch for northern corn rootworm

Variable	Coefficient Estimate	Standard Error
Intercept	5.382×10^{1}	3.133×10^{0}
CDD_{10} [a]	-1.358×10^{-2}	9.713×10^{-3}
Square of CDD_{10}	-1.700×10^{-5}	3.354×10^{-6}
Days soil temperature < 10 °C [b]	5.502×10^{-1}	7.226×10^{-2}
R^2	8.910×10^{-1}	

[a] Cooling degree days for base 10 °C accumulated from November 15 to the day of median egg hatch
[b] Counted for the 210 days before the day of median egg hatch

In Table 1 of their paper, Woodson and Ellsbury report the mean percent hatch for each treatment (each treatment had 5 or 10 replicates). These data were used to evaluate the new model by comparing its performance to the model of Woodson and Ellsbury. Table 3.13 reports the root of the mean square error (RMSE) and the mean absolute deviation (MAD) for each model relative to the data reported in Table 1 of Woodson and Ellsbury. In addition, the same criteria were used to evaluate the performance of the new model relative to the original model of Woodson and Ellsbury. These results are also included in Table 3.13. As expected, the new model does not fit the Table 1 data as well as the model of Woodson and Ellsbury. A better fit would result if the original data were used to estimate the new model. The plots in Figure 3.12 illustrate graphically the fits provided by each model relative to the data and to each other, and indicate that the new model performs adequately.

Table 3.13. Evaluation and comparison of Woodson and Ellsbury's (1994) model and new model of percent egg hatch for northern corn rootworm

Comparison	MAD[a]	RMSE[b]
W&E[c] model relative to W&E Table 1 data	4.47	5.85
Equation (3.49) model relative to W&E Table 1 data	6.90	8.17
Equation (3.49) model relative to W&E model	4.72	5.66

[a] Mean Absolute Deviation
[b] Root of the Mean Square Error
[c] W&E abbreviates Woodson and Ellsbury (1994)

Fisher (1989) reports a mean percent hatch of 58% ± 12% for northern corn rootworm eggs overwintered and hatched under field conditions near Brookings. Woodson et al. (1996) report a mean hatch percent of 74% and a range of 56%-81% for laboratory hatched post diapause northern corn rootworm eggs. Using these data as guides, the percent hatch was truncated at 85% to prevent unrealistically high hatches from occurring, since equation (4.49) can predict a hatch percent > 100% if CDD_{10} is low and STD_{10} is high, as can occur during unusually warm winters. After conducting numerous simulations using this model, for Brookings the average percent hatch was 53%, and 81% for Boone.

The initial larval population (P^{Larvae}) is the product of the previous year's total oviposition (P^{Eggs}_{Total}) and the percent hatch, divided by 100 to convert the percent to a decimal:

$$P^{Larvae} = \frac{H}{100} P^{Eggs}_{Total} . \tag{3.50}$$

This is then used to determine the total number of larvae that survive and emerge as adults in the current year.

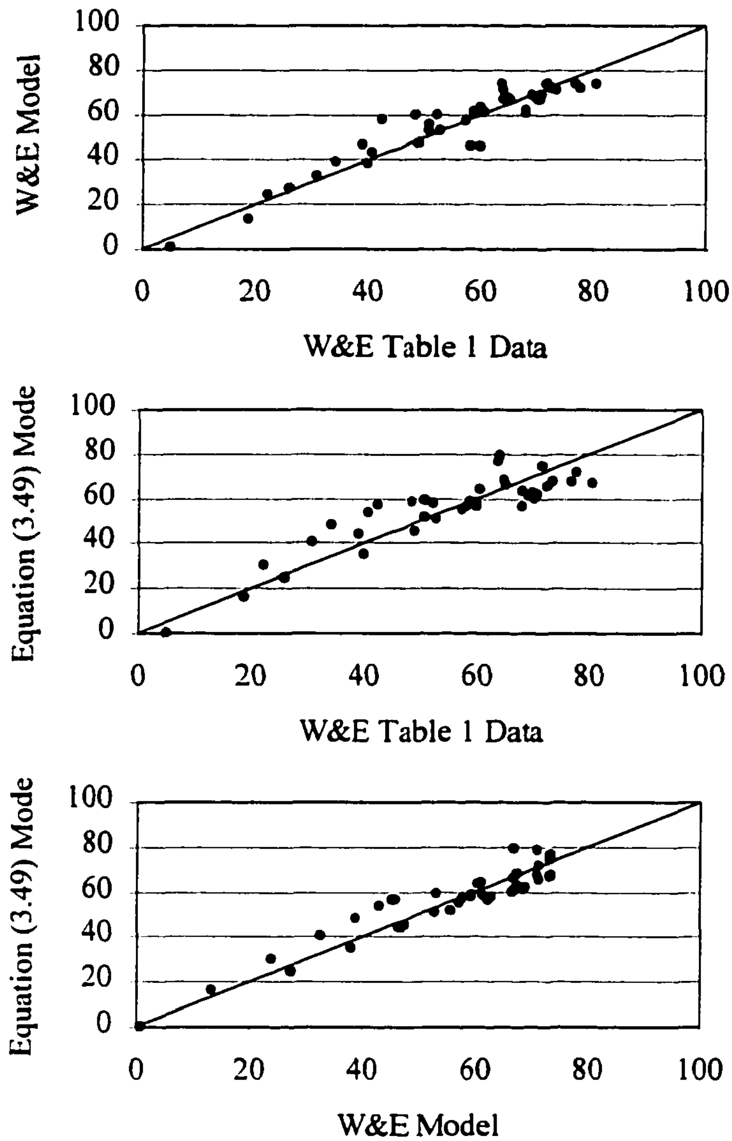


Figure 3.12. Plots of Woodson and Ellsbury (1994) and Equation (3.49) model predictions against Woodson and Ellsbury Table 1 data (top and middle) and plot comparing model predictions (bottom)

3.3.3.3 Model of Larval Survival to Emergence

Researchers have developed models of larval development (e.g. Woodson and Jackson 1996, Jackson and Elliot 1988), but these do not include a survival component that accounts for mortality. Elliot et al. (1988) conducted field research on the survival of larvae to adult emergence using the standard artificial infestation technique, but they did not develop a model. Woodson (1993, 1994) conducted similar research in a highly artificial laboratory environment, but also did not develop a model. The model for the percent of larvae that survive and emerge as adults used here was estimated using data from three years of field studies (1990-1991) conducted by Walt Riedell at the Northern Grains Insects Research Laboratory in Brookings, SD. Walt Riedell was generous enough to provide the complete data set from all the field experiments. See Riedell et al. (1996) for a complete description of the experiment and a summary of the results.

Western corn rootworm eggs with known percent hatch were placed in the soil to obtain experimentally controlled initial populations of larvae in a corn field. Among the data collected were the percent of larvae that survived and emerged from the soil as adults. Table 3.14 summarizes the experimental data used in this section. Following the lead of Elliot et al. (1988) and Woodson (1993, 1994), a density dependent survival function seemed best. However, because a deterministic model ignores the tremendous variation of the percent survival observed for the same initial larval population, a stochastic survival function was estimated. Since survival must be between 0% and 100% and exploratory histograms showed that the data were unimodally distributed, a beta density function was chosen:

Table 3.14. Summary of experimental data from Riedell et al. (1996)

Initial Larval Population	Average Survival[a]	Standard Deviation[a]
(larvae/m^2)	(%)	(%)
1200	6.05	4.29
2400	3.53	2.25
4800	2.27	1.17

[a] There are 24 observations for each initial larval population, for a total of 72 observations.

$$b(s) = \frac{\left(s^{\alpha-1}(1-s)^{\omega-1}\right)\Gamma(\alpha+\omega)}{\Gamma(\alpha)\Gamma(\omega)} \tag{3.51}$$

where s is the proportion of the initial larval population surviving to emerge as adults, Γ is the gamma function, and α and ω are the parameters of the beta density to be estimated.

To capture the effect of population density, the parameters of the beta density function were estimated as functions of the initial larval population. Various functions were tried and evaluated for statistical significance. The model that was chosen used a constant estimate for α and a linear function for ω:

$$\omega = \omega_0 + \omega_1 P^{larvae} \tag{3.52}$$

The parameters of the resulting composite function were estimated via maximum likelihood in TSP. The parameter estimates and associated standard errors are reported in Table 3.15. Figure 3.13 illustrates the density function and the effect of varying the initial larval population. Clearly increasing the initial larval population decreases both the mean and the variance of larval survival.

Using the initial larval population (P^{larvae}), the proportion of larvae that survive to emerge as adults (s) is drawn from the appropriately parameterized beta density. Next E_{Total}, the total number of adults that emerge, is determined as follows:

$$E_{Total} = sP^{larvae} \tag{3.53}$$

Table 3.15. Parameter estimates for the conditional beta density function for larval survival

Parameter[a]	Estimate	Standard Error[b]
α	2.926×10^{0}	6.091×10^{-1}
ω_0	1.830×10^{1}	8.066×10^{0}
ω_1	2.344×10^{-2}	7.348×10^{-3}

[a] See equations (3.52) and (3.53) for meaning and definition of parameters.
[b] Computed according to the method of Berndt et al. (1974).

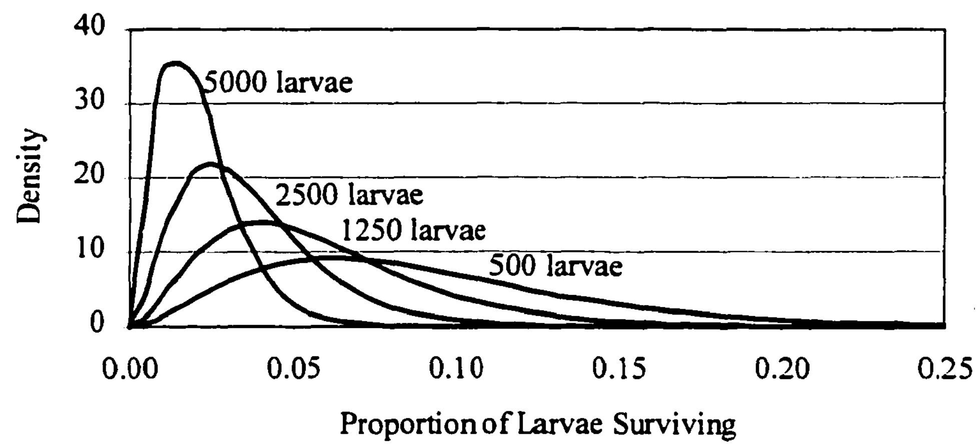


Figure 3.13. Conditional beta density function for proportion of larvae surviving and the effect of increasing the initial larval population

This equation links the larval survival model to the adult population and oviposition model through equations (3.31)–(3.32).

3.3.3.4 Summary of Egg Hatch and Larval Survival Model

This section described the models of egg hatch and larval survival that, with the adult population and oviposition model, provide a complete model of the corn rootworm life cycle. The model of egg hatch determines the percent of the previous season's eggs that hatch as a function of the soil temperature environment. As a result, egg hatch is stochastic since soil temperature is stochastic. The model of larval survival determines the proportion of larvae that survive to emerge as adults by incorporating the effect of larval population density into a conditional beta density function. As a result, larval survival is stochastic as well.

3.4 Conclusion

This chapter presented a detailed description of the stochastic weather generator and population model used for this study. The weather generator uses a Markov-exponential model for precipitation and a correlated residuals model for daily air temperatures, both adapted from Richardson (1981). The soil temperature model uses a modified form of the model of Potter and Williams (1994). The required inputs for using the weather generator are the coefficients for the numerous Fourier series and the elements of the correlation matrices. Methods for estimating these from daily weather data are described and the values used for Brookings, SD and Boone, IA are reported.

The corn rootworm population model is stochastic primarily because the weather variables that drive the corn rootworm life cycle models are stochastic. The multiple cohort model of adult population dynamics and oviposition was adapted from Naranjo and Sawyer (1989a), while the temperature dependent model of egg hatch was adapted from Woodson et al. (1996) and Woodson and Ellsbury (1994). The density dependent model of larval survival was developed from experimental data provided by Walt Riedell at the Northern Grains Insect Research Laboratory in Brookings, SD (Riedell et al. 1996). Required inputs for using the population model are the various daily weather data obtained from the weather generator, as well as all the parameter values given in the model description. In addition, the Julian day for the plant day and the day of peak flower are required.

Because the model is complex and time consuming to run, a simplification of the stochastics was necessary for performing the economic analysis. The next chapter describes this simplification as well as the estimation of stochastic damage functions.

CHAPTER 4: SIMPLIFIED CORN ROOTWORM POPUALTION MODEL AND STOCHASTIC MODEL OF ROOT RATING, LODGING, AND YIELD LOSS

4.1 Introduction

This chapter describes the estimation of several probability density functions for use in the subsequent Monte Carlo based economic analysis. The first section presents the estimation of three density functions that replace the stochastic dynamic corn rootworm population model. The next section presents the estimation of density functions for the root rating, lodging, and yield losses resulting from corn rootworm larval damage.

4.2 Simplified Stochastic Dynamic Corn Rootworm Population Model

4.2.1 Introduction

The stochastic corn rootworm population model presented in the previous chapter is difficult to use in a Monte Carlo based analysis, primarily because of the time needed to conduct several thousand simulations for each parameterization of the model. To simplify the model, simulations were conducted for a wide range of parameterizations and the results were used to estimate three density functions that describe the essential population dynamics. The simplified model focuses on the population at three stages—the total egg population at the end of the season, the initial larval population the following spring, and the maximum adult population the following summer. The total egg population at the end of the season is the total oviposition over the summer, the initial larval population is used to determine yield loss resulting from corn rootworm damage, and the maximum adult population is used to make insecticide application decisions the following spring as part of IPM. Figure 4.1 graphically illustrates how the simplified model proceeds. Each oval represents the total population of the specified type and the arrows between ovals represent the density functions

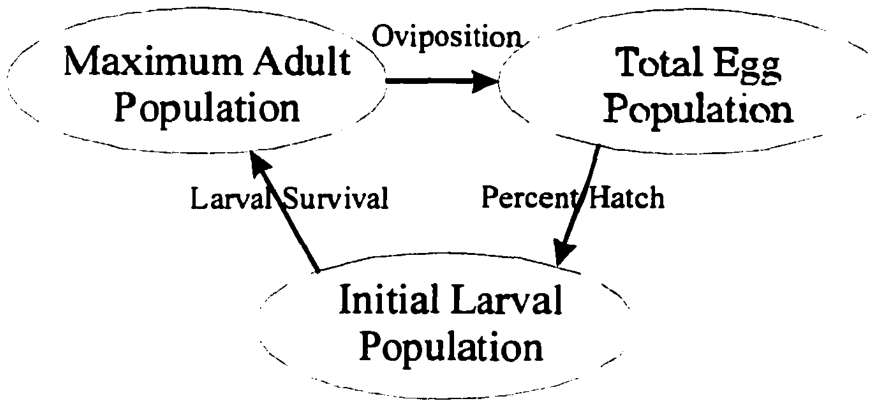


Figure 4.1. Illustration summarizing the simplified stochastic dynamic corn rootworm population model

describing the stochastic relationship between the populations. These density functions preserve the essentials of the more complex population model, yet can be integrated easily into a Monte Carlo analysis. What follows is a description of the simulation runs used to generate the data for density function estimation, followed by presentation of the estimation results for each density function.

4.2.2 Corn Rootworm Population Model Simulations

To generate sufficient data to accurately estimate the density functions describing the uncertainty of the population model, several thousand simulation runs were conducted. In general, all parameter values reported in chapter 3 were used for the weather generator and corn rootworm population model. The only inputs that were varied for simulations were the plant day and day of peak flower for corn.

The range of typical plant days for Brookings, SD is later than in Boone, IA. For Boone, earliest plantings occur in mid-April and most are completed by mid-May, while planting is about a week later in Brookings (Farnham 1997). For the simulations conducted for Boone, the earliest plant day was April 15 and the latest was May 13 (Julian days 105 and 133 respectively). For Brookings, the earliest plant day was April 23 and the latest was May 21 (Julian days 113 and 141 respectively). The day of peak flower for corn depends on the variety planted, the plant day, and the weather occurring after planting and is thus difficult to predict at plant. For the simulations conducted for Boone, the day of peak flowering ranges from July 4 to August 4 (Julian days 185 and 216 respectively), while for Brookings the range is July 20 to August 20 (Julian days 201 and 232 respectively). These ranges were developed from data reported by Naranjo and Sawyer (1989b), Spike and Tollefson (1989), and Ritchie and Hanway (1989).

In the sensitivity analysis of their model of adult corn rootworm population dynamics and oviposition, Naranjo and Sawyer (1989b) noted that model predictions were especially sensitive to day of peak flower, more so than to the plant day. As a result, the plant day was varied in four-day increments, while the day of peak flower was varied in one-day increments for each plant day. Varieties requiring more developmental time to flower yield more than varieties that require less time, but these higher yielding varieties must be planted earlier, or the corn will not fully mature before the first killing frost. Thus farmers who are able to plant early generally plant varieties requiring more developmental time, while those who plant later plant varieties requiring less developmental time. However, early planted corn still generally flowers before corn planted later, even though the corn planted later requires less developmental time. Taking this into account, simulations with early planted corn used only early days for the day of peak flower, and simulations with late planted corn used only late days for the day of peak flower. Table 4.1 summarizes the resulting 160 plant

Table 4.1. Plant day/day of peak flower combinations for which population model simulations were conducted

	Boone, IA		Brookings, SD	
Plant Day	Peak Flower Range	Combinations	Peak Flower Range	Combinations
105	185 to 200	16	-	-
109	185 to 200	16	-	-
113	185 to 208	24	201 to 216	16
117	185 to 208	24	201 to 216	16
121	193 to 216	24	201 to 224	24
125	193 to 216	24	201 to 224	24
129	201 to 216	16	209 to 232	24
133	201 to 216	16	209 to 232	24
137	-	-	217 to 232	16
141	-	-	217 to 232	16

day and peak flower day combinations for which simulations were conducted for each location.

Simulations were conducted for all 160 plant day/peak flower day combinations summarized in Table 4.1, assuming no soil insecticides were used. The initial number of eggs (P_{Total}^{Eggs}) was set at 1000 for the first year. The oviposition generated for each subsequent year was then passed to the next year as the value for P_{Total}^{Eggs}, creating a complete life cycle model. To obtain data for the population response to a wide variety of weather conditions, 100 years of weather were used for each plant day/peak flower day combination. With 160 plant day/peak flower day combinations and 100 years of weather, a total of 16,000 annual observations were generated for total oviposition, the initial larval population, and the maximum adult population. These data enable estimation of density functions for total oviposition, the initial larval population, and the maximum adult population when soil insecticides are not used. The impact of soil insecticides on population dynamics is included in the Monte Carlo analysis described in chapter 5.

4.2.3 Estimation of Corn Rootworm Population Density Functions

4.2.3.1 Percent Egg Hatch Density Function

Simulation results were used to estimate the unconditional density function for the proportion of eggs that hatch. Upon examining the histograms for both Brookings and Boone (Figure 4.2), the censoring of the data was apparent, especially for Boone. To prevent excessive hatch in unusually mild winters in the complex model, the percent of eggs that hatch was censored at 85%, the approximate maximum observed by Woodson and Ellsbury (1994) in laboratory experiments. From the data histograms, this upper limit was not

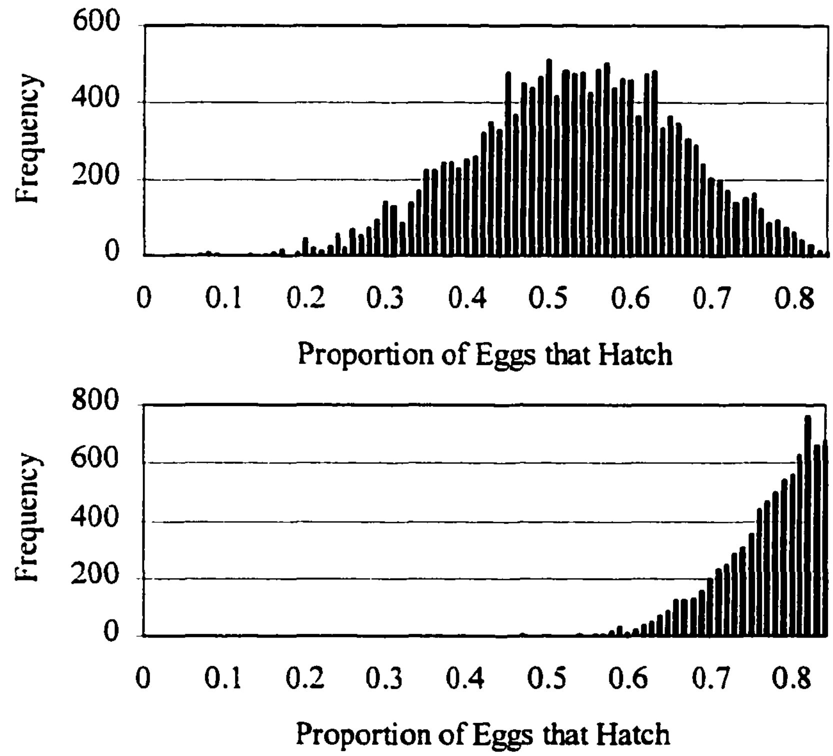


Figure 4.2. Histograms of uncensored hatch data from simulations for Brookings, SD (top) and Boone, IA (bottom)

particularly binding for Brookings, but greatly so for Boone. This occurs because the winters are relatively more mild in Boone compared to those in Brookings. See Table 4.2 for a summary of the censoring and sample means and standard deviations.

Data that have been censored from above can be modeled as follows:

$$h = \begin{cases} h^* & \text{if } h^* < c \\ c & \text{if } h^* \geq c \end{cases} \tag{4.1}$$

where h is the observed hatch, h^* is the underlying latent variable that determines the value of h, and c is the value at which h is censored (0.85). To estimate the density function of h, the density function of h^* is needed. Examining the histograms, it seems reasonable to assume that h^* follows the normal distribution with a mean μ_h and variance σ_h^2.

To estimate the parameters μ_h and σ_h, a method of moments (MOM) estimator was developed. Following Greene (1997) Theorem 20.3: If $h^* \sim N(\mu_h, \sigma_h^2)$ and h is determined according to equation (4.1), then:

$$E[h] = c(1 - \Phi(\alpha)) + \Phi(\alpha)(\mu_h - \sigma_h \lambda(\alpha)) \tag{4.2}$$

$$V[h] = \sigma_h^2 \Phi(\alpha)\left[(1 - \delta(\alpha)) + (\alpha - \lambda(\alpha))^2 (1 - \Phi(\alpha))\right] \tag{4.3}$$

Table 4.2. Sample statistics and parameter estimates for egg hatch density function

Sample Statistic or Parameter	Brookings, SD	Boone, IA
Censored Observations	47	7,651
Sample Mean	0.52783	0.80939
Sample Standard Deviation	0.12765	0.05766
MOM estimate of μ_h	0.52808	0.84562
MOM estimate of σ_h	0.12836	0.09621
$\Pr(h^* < 0.0)$	0.00002	0.00000
$\Pr(h^* > 0.85)$	0.00607	0.48184

E and V are the expectation and variance operators respectively, Φ and ϕ are the standard normal cumulative distribution and density functions respectively, and $\alpha = (c - \mu_h)/\sigma_h$, $\lambda(\alpha) = -\phi(\alpha)/\Phi(\alpha)$, and $\delta(\alpha) = \lambda(\alpha)(\lambda(\alpha) - \alpha)$. The MOM simply equates $E[h]$ and $V[h]$ to their sample analogues, the sample mean and variance, and solves the simultaneous equations for μ and σ. The sample statistics and the resulting MOM estimators are reported in Table 4.2.

The estimated parameters μ_h and σ_h are for the normal density function describing the distribution of h^*. To determine h for a year simply requires a draw from this normal density, then censoring it at $c = 0.85$ (and at zero as well). The probabilities of censoring are reported in Table 4.2 for both estimates of μ_h and σ_h. The model of egg hatch described in the previous chapter required daily output from the stochastic weather generator, a computationally intensive process. This egg hatch density function replaces this process with a single draw from a normal density function, thus simplifying this component of the stochastic population model and allowing easy integration into a Monte Carlo analysis.

4.2.3.2 Maximum Adult Population Conditional Density Function

Simulation results were used to estimate a density function for the maximum adult population (P^{Adults}_{Max}) conditional on the initial larval population (P^{Larvae}) and the plant day (J^{Plant}). Since the maximum adult population must be positive and has no theoretical upper bound, density functions such as the gamma or the log-normal seem appropriate. The gamma density was chosen and its parameters were estimated as functions of the plant day and the initial larval population. Various functions were estimated and evaluated for statistical significance and the following model for the conditional gamma density function was chosen:

$$d(P_{Max}^{Adults} \mid J^{Plant}, P^{Larvae}) = \frac{(P_{Max}^{Adults})^{\theta-1} \exp\left(-P_{Max}^{Adults} / \lambda\right)}{\lambda^{\theta}\Gamma(\theta)} \tag{4.4}$$

$$\theta = \theta_0 + \theta_{J1} J^{Plant} + \theta_{L1} P^{Larvae} + \theta_{L2} (P^{Larvae})^2 \tag{4.5}$$

$$\lambda = \lambda_0 + \lambda_{J1} J^{Plant} + \lambda_{L1} P^{Larvae} + \lambda_{L2} (P^{Larvae})^2 \tag{4.6}$$

Maximum likelihood estimates of the parameters and their standard errors are reported in Table 4.3. Figures 4.3 and 4.4 illustrate the conditional densities for Brookings and Boone and the effect of changing the plant day and the initial larval population. The density functions indicate that for equivalent conditions, the maximum adult population is likely to be higher in Boone. This occurs because of the warmer climate in Boone is more conducive to corn rootworm growth and development.

Table 4.3. Parameter estimates for maximum adult population density function

	Brookings, SD		Boone, IA	
Parameter[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
θ_0	-1.838×10^{-1}	2.720×10^{-1}	5.713×10^{-1}	2.955×10^{-1}
θ_{J1}	2.537×10^{-2}	2.194×10^{-3}	-3.391×10^{-2}	2.552×10^{-3}
θ_{L1}	-1.093×10^{-3}	2.667×10^{-4}	3.074×10^{-3}	4.511×10^{-5}
θ_{L2}	5.047×10^{-7}	2.968×10^{-7}	-3.738×10^{-7}	4.888×10^{-9}
λ_0	-2.629×10^{-1}	6.054×10^{-2}	-1.366×10^{1}	5.441×10^{-1}
λ_{J1}	1.758×10^{-3}	5.149×10^{-4}	1.407×10^{-1}	5.121×10^{-3}
λ_{L1}	2.871×10^{-2}	3.986×10^{-4}	8.033×10^{-3}	1.503×10^{-4}
λ_{L2}	-9.647×10^{-6}	5.307×10^{-7}	-9.325×10^{-7}	2.955×10^{-8}

[a] See equations (4.4) – (4.6) for meaning and definition of parameters.
[b] Computed according to the method of Berndt et al. (1974).

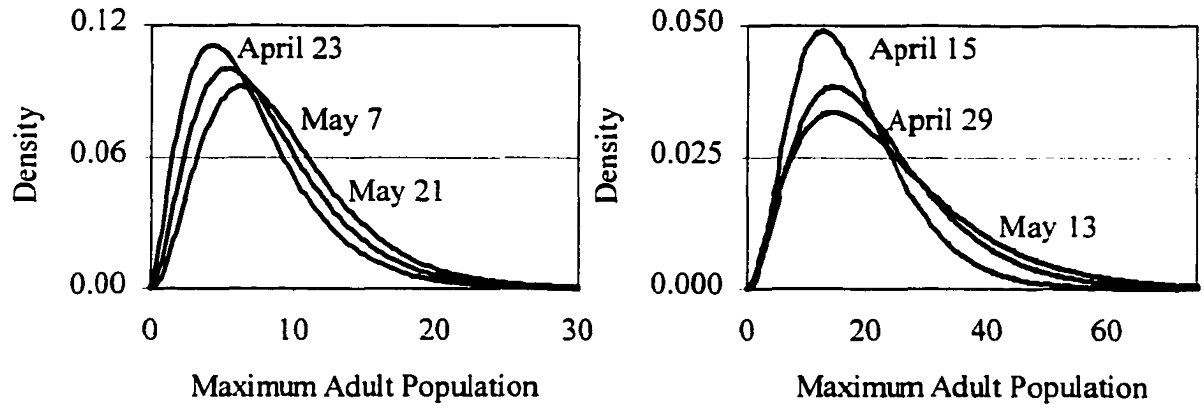


Figure 4.3. Effect of increasing plant day on the maximum adult population density function for Brookings (left) and Boone (right), with 100 and 500 initial larvae respectively

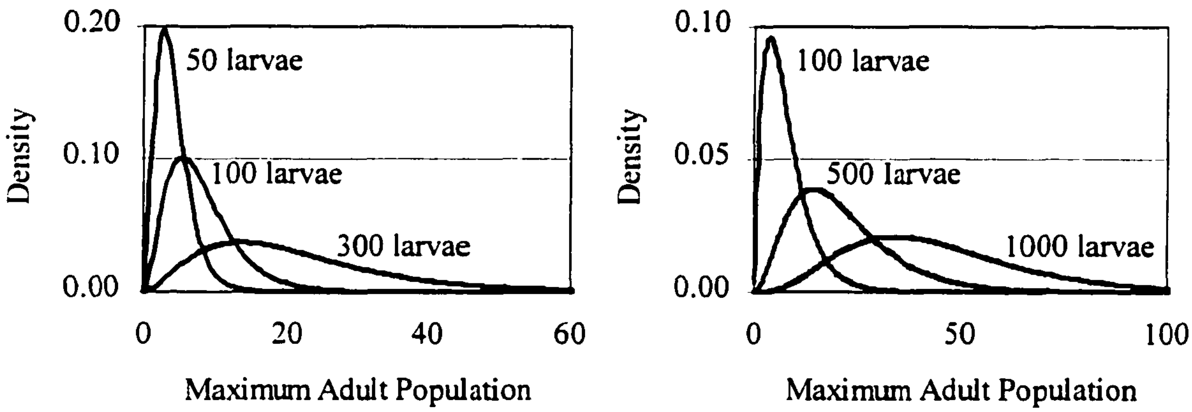


Figure 4.4. Effect of the initial larval population on the maximum adult population density function for Brookings (left) and Boone (right), for a May 7 and April 29 plant day respectively

As the plant day increases, the mean and variance of the maximum adult population increases in both locations. When corn is planted early, corn rootworm do not do well—adults are more likely to emerge as the proportion of corn plants flowering decreases and less food is available. With later plant dates, corn rootworm larvae are more likely to coordinate their emergence with peak corn flowering, so adult mortality is on average reduced and the mean observed maximum adult population increases. In years when weather events are particularly bad for corn rootworm, the maximum adult population is low for an equivalent initial larval population, regardless of the plant day. However, in years with good weather, corn rootworm emerging in fields of later planted corn find a better food supply and the maximum adult population is higher. As a result the variance must increase, since the probability of low adult populations remains nearly unchanged, but the probability of high adult populations increases.

Figure 4.4 illustrates effect changing the initial larval population has on the density for the maximum adult population for Brookings and Boone. Again the mean and the variance increase in both locations as the initial larval population increases. Intuitively, as the initial number of larvae increases, on average more adults emerge and the mean of the maximum number of adults observed increases. The variance increases as well, because in years with bad weather, adult populations are low regardless of the initial number of larvae, but in years with good weather, fields with more larvae have higher adult populations.

4.2.3.3 Oviposition Conditional Density Function

Simulation results were used to estimate a density function for the total annual oviposition (P_{Total}^{Eggs}) conditional on the maximum adult population (P_{Max}^{Adults}) and the plant day (J^{Plant}). Since oviposition must be positive and has no theoretical upper bound, density functions such as the gamma or the log-normal are appropriate. Again the gamma density function was chosen and its parameters were estimated as functions of the maximum adult population and the plant day. Various functions were estimated and evaluated for statistical significance and the following model for the conditional gamma density function was chosen:

$$q(P_{Total}^{Eggs} \mid P_{Max}^{Adults}, J^{Plant}) = \frac{(P_{Total}^{Eggs})^{\theta-1} \exp\left(-P_{Total}^{Eggs} / \lambda\right)}{\lambda^{\theta}\Gamma(\theta)} \tag{4.7}$$

$$\theta = \theta_0 + \theta_{J1} J^{Plant} + \theta_{J2}(J^{Plant})^2 + \theta_{A1} P_{Max}^{Adults} \tag{4.8}$$

$$\lambda = \lambda_0 + \lambda_{J1} J^{Plant} + \lambda_{J2}(J^{Plant})^2 + \lambda_{A1} P_{Max}^{Adults} \tag{4.9}$$

Maximum likelihood estimates of the parameters and their standard errors are reported in Table 4.4. Figures 4.5 and 4.6 illustrate the conditional densities for Brookings and Boone and the effect of changing the plant day and the maximum adult population. Boone has a noticeably larger mean and variance of oviposition, because its relatively warmer weather is more conducive to corn rootworm growth.

The mean and variance of oviposition increase in both locations as the plant day increases. As previously discussed, when corn is planted early, corn rootworm adults are less able to coordinate their emergence with the period of corn flowering, so less food is available. Thus mortality is higher, fewer females survive, and mean oviposition is reduced.

Table 4.4. Parameter estimates for conditional oviposition density function

	Brookings, SD		Boone, IA	
Parameter[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
θ_0	1.829×10^{1}	7.166×10^{0}	4.298×10^{1}	1.519×10^{1}
θ_{J1}	-2.695×10^{-1}	1.142×10^{-1}	-7.094×10^{-1}	2.576×10^{-1}
θ_{J2}	1.017×10^{-3}	4.536×10^{-4}	2.951×10^{-3}	1.088×10^{-3}
θ_{A1}	2.590×10^{-1}	2.670×10^{-3}	2.278×10^{-1}	3.464×10^{-3}
λ_0	-9.005×10^{2}	1.208×10^{2}	-5.427×10^{2}	1.936×10^{2}
λ_{J1}	1.310×10^{1}	1.910×10^{0}	7.932×10^{1}	3.291×10^{0}
λ_{J2}	-4.233×10^{-2}	7.527×10^{-3}	-1.779×10^{-2}	1.394×10^{-2}
λ_{A1}	6.097×10^{-1}	1.863×10^{-2}	4.457×10^{-1}	1.718×10^{-2}

[a] See equations (4.7) – (4.9) for meaning and definition of parameters.
[b] Computed according to the method of Berndt et al. (1974).

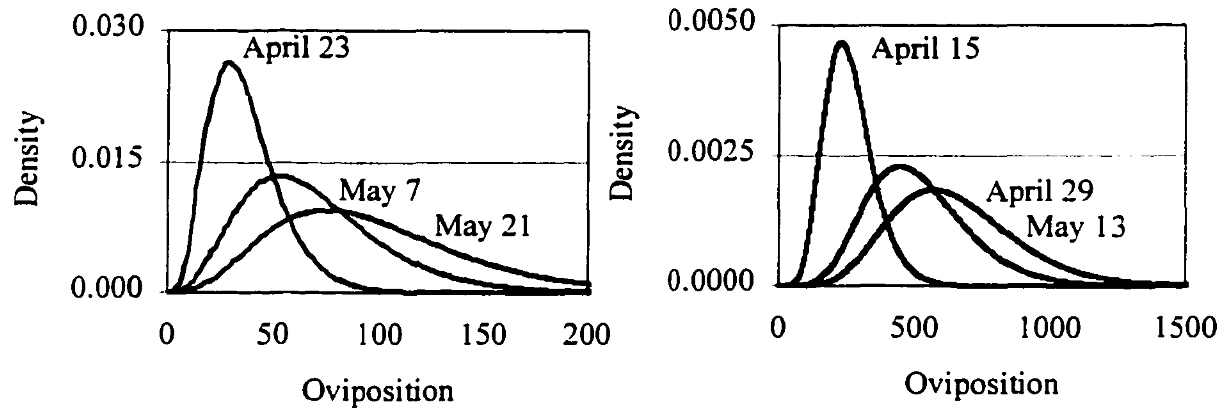


Figure 4.5. Effect of increasing the plant day on the conditional oviposition density function for Brookings (left) and Boone (right), with 4.4 and 23 adults per square meter respectively

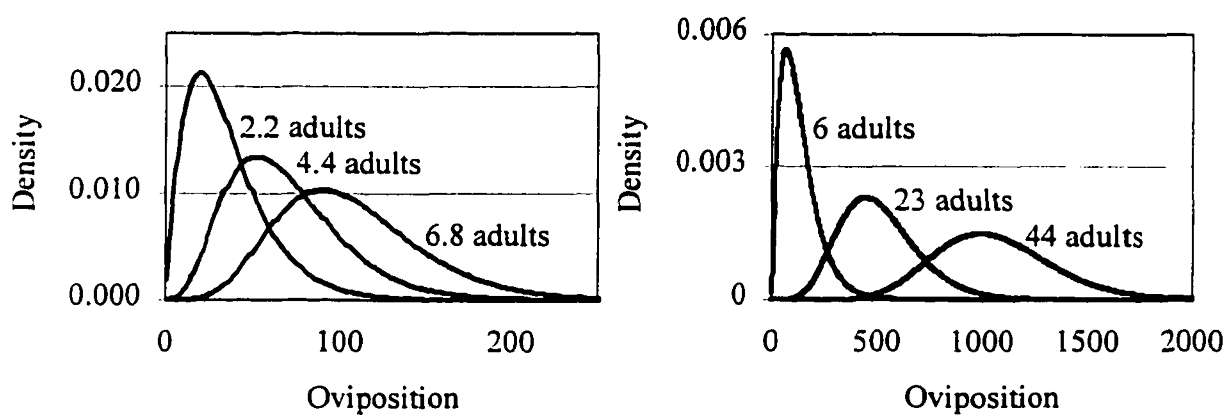


Figure 4.6. Effect of increasing the maximum adult population on the conditional oviposition density function for Brookings (left) and Boone (right), for a May 7 and April 29 plant day respectively

In years with bad weather, few eggs are laid regardless of the plant day, but in good years, more eggs are likely to be laid in later planted fields. As a result, the variance must increase. The mean and variance of oviposition also increase as the maximum adult population increases. The increase of the mean is intuitive—more adults imply that on average more eggs are likely to be laid. However, this increase in the mean is associated with an increase in the variance, indicating that other factors besides the size of the adult population become more important determinants of the total oviposition.

4.3 Root Rating, Lodging, and Yield Loss Density Functions

4.3.1 Introduction

This section reports parameter estimates for conditional density functions describing root rating, lodging, and the associated yield loss. The experimental data used to estimate these parameters were obtained from Walt Riedell at the USDA-ARS Northern Grain Insect Research Laboratory in Brookings, SD. For three years (1990-1992), field plots were artificially infested with experimentally controlled initial larval populations at four levels (0, 1200, 2400, and 4800 larvae per meter of row). Among the data collected were the root rating (on the 1-9 scale), percent of stand lodged, adults surviving to emergence, and yield. Average yields for control plots ranged from 99.1% to 93.7% of NASS county average yields reported for Brookings county each year. See Riedell et al. (1996) for a complete description of the experiment and summary of results.

4.3.2 Root Rating Conditional Density Function

4.3.2.1 Conditional MOM Parameter Estimates

As measures of corn rootworm larval feeding damage, root ratings are highly dependent on the initial larval population. However, this relationship is far from deterministic, since other factors influence the root rating. Conditional histograms showed that the density was both unimodal and J shaped, depending on the initial larval population. Furthermore, by definition a root rating must range between 1 and 9. The beta density was chosen as the underlying density function because it is sufficiently flexible and has lower and upper limits. However, the method of maximum likelihood could not be used since the likelihood function is not concave when the beta density is U or J shaped (Nelson and Preckel 1989). The method of moments (MOM) estimator was used (Evans et al. 1993), which estimates the parameters of the beta density as functions of the sample mean and variance. To capture the effect of the initial larval population, the mean and variance were modeled as functions of this population. What follows is a description of the conditional model for the mean and variance, then the MOM estimation process.

The observed root ratings were normalized to a 0-1 scale, then the sample mean and variance of this normalized root rating were calculated for each of the four initial larval populations. There were 54 observations in each treatment, for a total of 216 observations. Figure 4.7 plots the results against the initial larval population. A negative exponential model was chosen for the conditional mean, since it asymptotically approaches the maximum of one and requires only one parameter. An ordinary least squares (OLS) criterion was used to estimate the following model:

$$m_R = 1 - \exp\left(-\nu P^{Larvae}\right) \tag{4.10}$$

where m_R is the observed root rating, P^{Larvae} is the initial larval population, and ν is the estimated parameter. The OLS parameter estimate for ν is 4.987 x 10^{-4} and the resulting fit is illustrated in Figure 4.7.

A quadratic spline technique was used to smooth the conditional variance (s_R^2) and preserve its rapid rise and gradual decline. Figure 4.7 illustrates the resulting fit and Table 4.5 reports the coefficients. Specifically, three quadratic equations were fit to the data points to generate the following model:

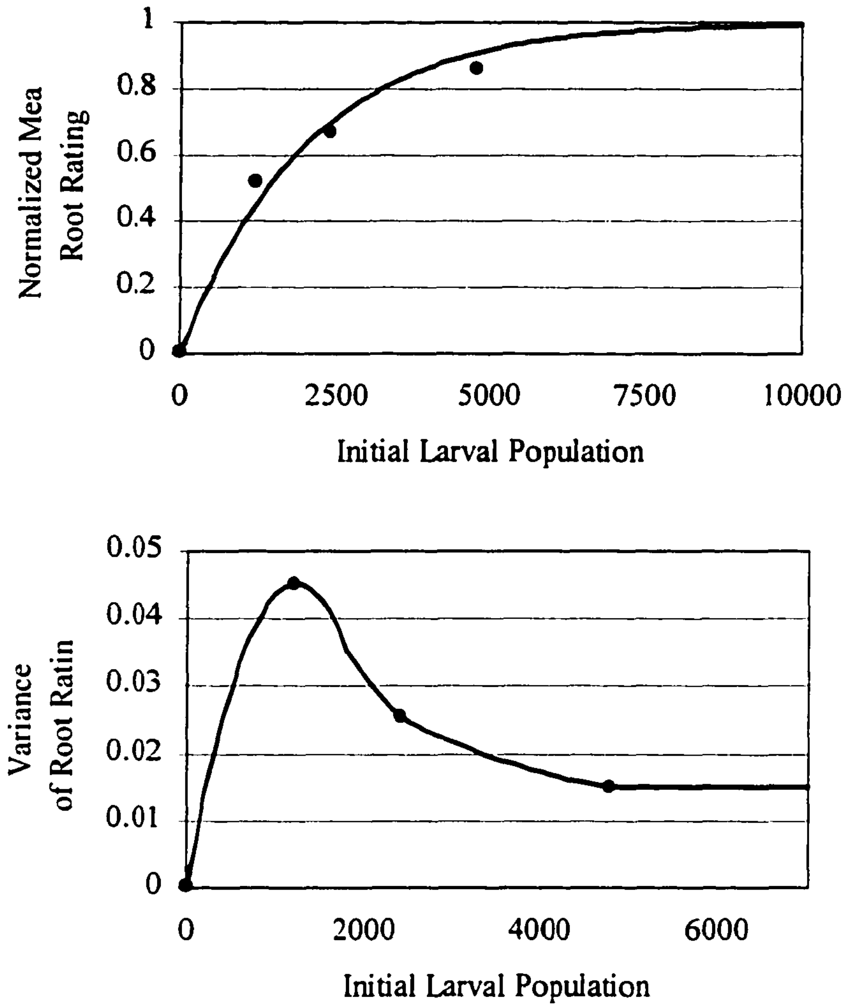


Figure 4.7. Observed and fitted mean and standard deviation of normalized root ratings conditional on the initial larval population

Table 4.5. Quadratic spline coefficients for equation (4.11)

Coefficient	Value	Coefficient	Value	Coefficient	Value
a_1	0.00021	b_1	7.35×10^{-5}	c_1	-3.00×10^{-8}
a_2	0.09433	b_2	-4.50×10^{-5}	c_2	6.78×10^{-9}
a_3	0.04616	b_3	-1.08×10^{-5}	c_3	9.03×10^{-10}
a_4	0.01495				

$$s_R^2 = \begin{cases} a_1 + b_1 P^{Larvae} + c_1 (P^{Larvae})^2 & \text{if } 0 < P^{Larvae} \leq 1800 \\ a_2 + b_2 P^{Larvae} + c_2 (P^{Larvae})^2 & \text{if } 1800 < P^{Larvae} \leq 2400 \\ a_3 + b_3 P^{Larvae} + c_3 (P^{Larvae})^2 & \text{if } 2400 < P^{Larvae} \leq 4800 \\ a_4 & \text{if } 4800 < P^{Larvae} \end{cases} \tag{4.11}$$

These functions determine the conditional mean and variance of the normalized root rating. The MOM estimators of the parameters of the beta density function (α and ω) are functions of this conditional mean and variance and thus also depend on the initial larval population. The conditional beta density function of the normalized root rating—$b(R \mid P^{larvae})$—and the MOM estimators of α and ω are summarized by the following equations:

$$b(R \mid P^{larvae}) = \frac{R^{\alpha-1}(1-R)^{\omega-1}\Gamma(\alpha+\omega)}{\Gamma(\alpha)\Gamma(\omega)} \tag{4.12}$$

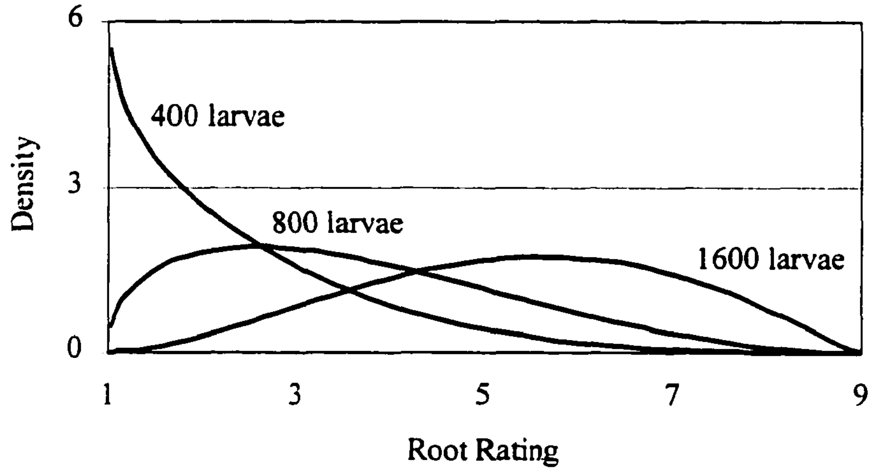
$$\alpha = m_R\left(\frac{m_R(1-m_R)}{s_R^2} - 1\right) \tag{4.13}$$

$$\omega = (1-m_R)\left(\frac{m_R(1-m_R)}{s_R^2} - 1\right) \tag{4.14}$$

Figure 4.8 illustrates the resulting density function and the effect of increasing the initial larval population. Clearly as the larval population increases, the density function shifts right and switches from an inverse J shape, to a unimodal shape, to a J shape, which is consistent with the conditional histograms.

4.3.2.2 Derivation of Insecticide Efficacy

The conditional mean function of equation (4.10) was used in conjunction with reported field data to derive an estimate of the efficacy of corn rootworm soil insecticides for use in the Monte Carlo based analysis of IPM and IPM insurance described in chapter 5.



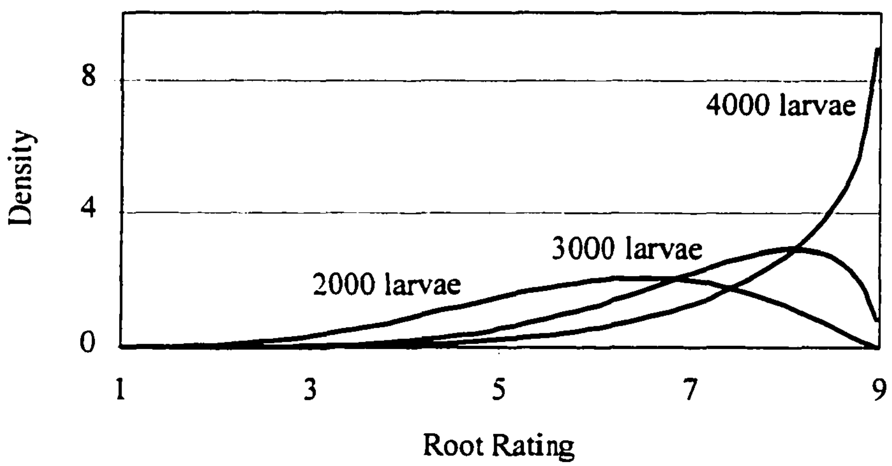


Figure 4.8. Effect of increasing the initial larval population on the conditional beta density function for root rating

A pesticide's efficacy is the percent of the pest population which it kills. Iowa State University Department of Entomology has been conducting extensive and long-term evaluation of corn insecticides. For untreated plots through out the state, Rice (1997) reported a five year average root rating of 4.55 on the 1-6 scale. Using Oleson's (1998) conversion chart, this is a 7.5 on the 1-9 scale. Inverting equation (4.10), this implies an initial larval population of 1400. Tollefson (1998) reports root ratings for field evaluations of several soil insecticides. Good control under high corn root worm pressure typically results in a root rating of 2 on the 1-6 scale. Again using Oleson's conversion chart, this is a 3-4 on the 1-9 scale. Inverting equation (4.10) for root ratings of 3.0, 3.5 and 4.0 gives initial larval populations of 240, 390, and 480 respectively. These imply efficacies of 83%, 72% and 66% respectively. The average of these three is 74%, which was rounded to 75% and was used in all simulations for the efficacy of soil insecticides.

4.3.3 Lodging Conditional Density Function

The data obtained from Walt Riedell (Riedell et al. 1996) were also used to estimate a density function of lodging conditional on the initial larval population. Lodging is reported as the percent of the corn plants that are lodged, and as such is limited to the range 0%-100%. Originally, a beta density function was assumed and a conditional MOM estimation procedure was used just as for the root rating density function. However, this resulted in U shaped density functions that implied positive probabilities for very low lodging when larval populations were relatively high. This is counterintuitive and had no support in the data. An alternative is to assume that the data are censored observations of an underlying conditional density. Data that are censored both from above and below can be modeled as follows:

$$L = \begin{cases} c_L & \text{if } L^* \le c_L \\ L^* & \text{if } c_L < L^* < c_U \\ c_U & \text{if } L^* \ge c_U \end{cases} \tag{4.15}$$

where L is the observed lodging and L^* is the underlying latent variable that determines L, and c_L and c_U are the lower and upper values at which L is censored. Here $c_L = 0$ and $c_U = 100$.

To estimate the density of L, the density of L^{*} is needed. Since the data were unimodal at moderate larval populations, a normal density was assumed. Furthermore, since observed lodging depends on the initial larval population, the parameters of the normal density function of L^{*} were modeled as functions of this population. This implies estimating a doubly censored Tobit model with heteroscedasticity. The log-likelihood function and the conditional equations for μ_L and σ_L, the parameters of the normal density of L^{*}, are:

$$\ln L(L \mid P^{larvae}) = \sum_{L \le c_L} \ln\left(\Phi\left(\frac{c_L - \mu_L}{\sigma_L}\right)\right) + \sum_{c_L < L < c_U} -0.5\left(\ln(2\pi) + \ln(\sigma_L^2) + \frac{(L - \mu_L)^2}{\sigma_L^2}\right) + \sum_{L \le c_L} \ln\left(1 - \Phi\left(\frac{c_U - \mu_L}{\sigma_L}\right)\right) \tag{4.16}$$

$$\mu_L = m_0 + m_1 P^{larvae} \tag{4.17}$$

$$\sigma_L = s_0 + s_1 P^{larvae} \tag{4.18}$$

Table 4.6 reports the maximum likelihood estimates for the parameters and Figure 4.9 illustrates the resulting conditional density function and the effect of increasing the initial larval population. As expected, the density function shifts to the right as the larval population increases, so that the probability lodging increases.

Table 4.6. Parameter estimates for censored normal density function for lodging conditional on initial larval population

Parameter[a]	Estimate	Standard Error[b]
m_0	-2.665×10^{1}	6.594×10^{0}
m_1	2.494×10^{-2}	2.251×10^{-3}
s_0	3.362×10^{1}	4.960×10^{0}
s_1	2.177×10^{-3}	2.022×10^{-3}

[a] See equations (4.16) – (4.18) for meaning and definition of parameters.
[b] Computed according to the method of Berndt et al. (1974).

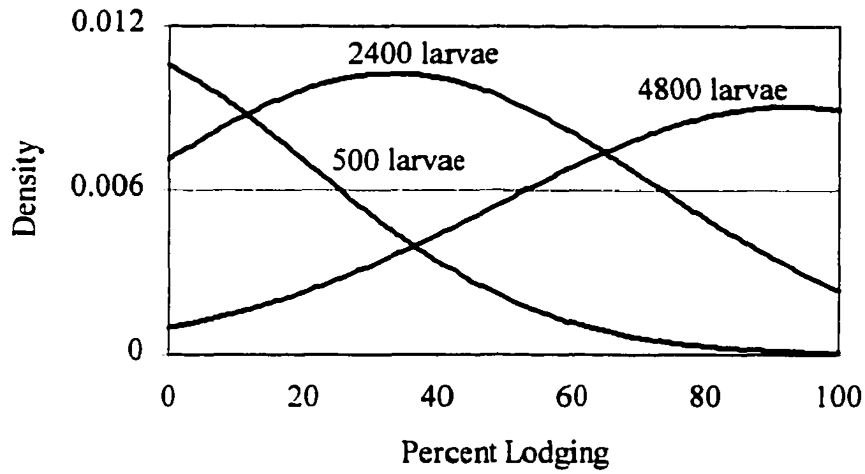


Figure 4.9. Effect of increasing the initial larval population on the censored normal density function for lodging, where the probability of left censoring is 0.66, 0.20, and 0.02 and the probability of right censoring is 0.00, 0.04 and 0.44, for larvae of 500, 2400, and 4800 respectively

4.3.4 Yield Loss Conditional Density Function

The data provided by Walt Riedell (Riedell et al. 1996) were used to estimate the proportion of yield loss conditional on the root rating and percent lodging. A higher root rating implies greater root damage and thus increased yield loss. Lodging also reduces yields/increases yield loss independent of root damage (Spike and Tollefson 1991). The average yield for control plots—plots with initial larval populations of zero—were used as estimates of the pest free yield (y_{pf}) for each year. There were 18 control plot observations for each year. The proportion of yield loss (p_{loss}) for all 216 experimental plots was calculated as follows:

$$p_{loss} = \frac{y_{pf} - y_{obs}}{y_{pf}} \tag{4.19}$$

where y_{obs} is the observed yield and y_{pf} is the pest free yield appropriate for the year.

Because information on the root rating and/or lodging may be ignored or may not be available, three density functions were estimated: one conditional on root rating only, one conditional on lodging only, and one conditional on both root rating and lodging. A simple linear regression was used to estimate the proportion of yield loss as a function of the observed root rating and percent lodging. Upon examining the residual plots, heteroscedasticity was apparent. As a result, a maximum likelihood model was specified with normal errors and a variance specification depending on the root rating and the percent lodging. The log-likelihood function and the general model for parameter dependence on the root rating and lodging are:

$$\ln L(p_{loss} \mid R, L) = \sum -0.5\left(\ln(2\pi) + \ln(\sigma_p^2) + \frac{(p_{loss} - \mu_p)^2}{\sigma_p^2}\right) \tag{4.20}$$

$$\mu_p = m_R(R-1) + m_L L \tag{4.21}$$

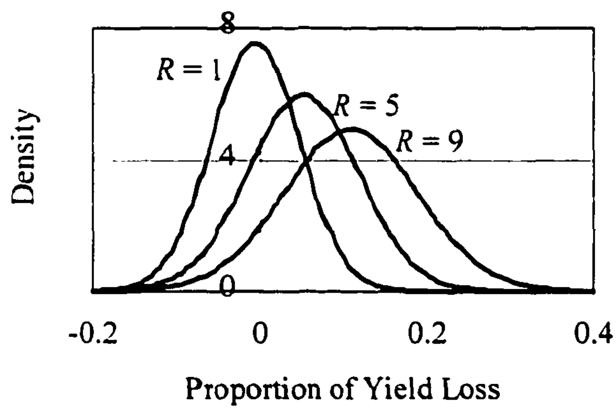
$$\sigma_p = s_0 + s_R R + s_L L \tag{4.22}$$

To estimate the less informed models, m_R and s_R, or m_L and s_L, were restricted to zero as was appropriate. Equation (4.21) imposes the restriction that when the root rating is 1.0 and/or the lodging is 0%, that the expected yield loss is zero. Table 4.7 reports the maximum likelihood estimates and standard errors for all three models. Figures 4.10 and 4.11 illustrate the conditional densities and the effect of changing the root rating and lodging. Figure 4.10 indicates that there is little difference in mean and variance for the less informed density functions as the conditioning variable changes from its minimum to its mean to its maximum. In Figure 4.11 the left plot shows the effect of changing the root rating from its mean with lodging held at its mean of 35% and the right plot shows the effect of changing

Table 4.7. Parameter estimates for the three proportion of yield loss density functions conditional on root rating and percent lodging

Model	Parameter[a]	Estimate	Standard Error[b]
Without Lodging	m_R	1.335×10^{-2}	1.035×10^{-3}
	s_0	4.913×10^{-2}	5.548×10^{-3}
	s_R	3.591×10^{-3}	1.047×10^{-4}
Without Root Rating	m_L	1.383×10^{-3}	1.317×10^{-4}
	s_0	5.390×10^{-2}	2.702×10^{-3}
	s_L	2.500×10^{-4}	7.217×10^{-5}
Lodging and Root Rating	m_R	4.334×10^{-3}	1.518×10^{-3}
	m_L	1.006×10^{-3}	1.667×10^{-4}
	s_0	5.507×10^{-2}	6.142×10^{-3}
	s_R	-1.019×10^{-3}	1.730×10^{-3}
	s_L	3.425×10^{-4}	1.487×10^{-4}

[a] See equations (4.20) – (4.22) for meaning and definition of parameters.
[b] Computed according to the method of Berndt et al. (1974).



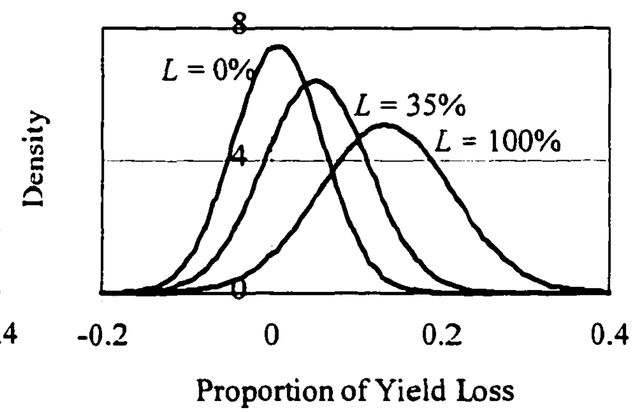


Figure 4.10. Effect of increasing root rating (R) on the proportion of yield loss density function conditional only on root rating (left) and the effect of increasing lodging (L) on the proportion of yield loss density function conditional only on lodging (right)

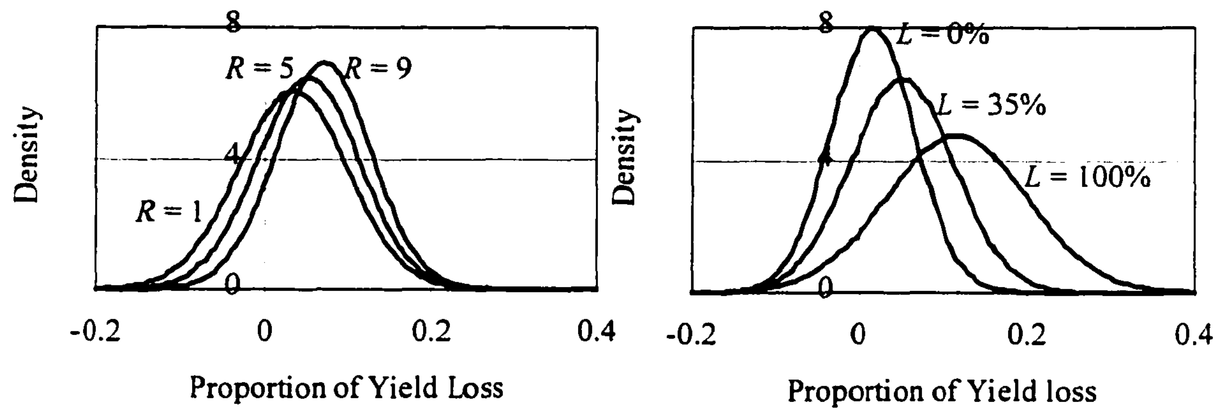


Figure 4.11. Effect of increasing the root rating (R) with lodging fixed at 35% (left) and the effect of increasing lodging (L) with the root rating fixed at 5 (right) on the proportion of yield loss density function conditional on both root rating and lodging

lodging from its mean with the root rating held at its mean of 5. The plots reveal that lodging has a greater effect on the mean and variance of yield loss than the root rating. Both the mean and variance increase as lodging increases with a fixed root rating. However, the mean increases and the variance decreases as the root rating increases with a fixed lodging.

4.4 Summary

This chapter described the estimation of the parameters of several density functions for use in subsequent Monte Carlo based economic analysis. Using simulation data, three density functions were estimated to create a simplified stochastic dynamic corn rootworm population model. The percent of eggs that hatch each year is a random draw from an unconditional censored normal density. The initial larval population each year is then obtained by converting this percentage to a proportion and multiplying by the previous year's total oviposition. The maximum adult population realized from this initial larval population is then obtained as a random draw from a gamma density function conditioned on this initial larval population and the plant day. The total oviposition for the year is then obtained as a random draw from a gamma density function conditioned on this maximum adult population and plant day. The initial larval population for the next year is then the product of the random proportion of eggs that hatch and the total oviposition for the previous year. This describes the steps of the stochastic dynamic population model summarized in Figure 4.1.

Data provided by Walt Riedell were also used to estimate three density functions that describe the uncertainty inherent in using root ratings and observed percent lodging as measures of corn rootworm population and yield losses from corn rootworm damage. A beta density function conditional on the initial larval population describes the root rating uncertainty. Lodging uncertainty is described with a doubly censored normal density function conditional on the initial larval population. Lastly, a normal density with a mean and variance conditional on the root rating and percent lodging describes the proportion of yield lost due to corn rootworm damage.

CHAPTER 5: EMPIRICAL ANALYSIS OF CORN ROOTWORM IPM INSURANCE

5.1 Introduction

Chapter 2 presented a general theoretical model that captured the essence of the problem faced by producers. However for relevant empirical analysis, a specific model is desired that accurately reflects a real problem producers face. Chapter 1 included a general overview of the corn rootworm problem faced by corn producers and a simple description of how IPM insurance works. Chapters 3 and 4 developed a specific model of the stochastic production process and the impact of corn rootworm. This chapter links this production model with a formal model of IPM insurance, which allows empirical estimation of the sign and magnitude of some of the theoretical effects of IPM and insurance on adoption incentives and optimal input use discussed in chapter 2.

First model details and notation are presented. As an extension to a specific case, the simplicity of the general model is lost, but the core model remains the same as is illustrated in the model presentation. Next the Monte Carlo technique used for the empirical analysis is described along with the algorithms used for random number generation. Next empirical findings concerning the value of IPM to producers and the effect of IPM adoption on optimal insecticide use are presented, then the value of IPM insurance and its risk effect on optimal insecticide use. In general, the empirical findings indicate that IPM has sufficient value to producers to cover the cost of implementation and IPM greatly reduces optimal insecticide use. However, IPM insurance has little value to producers because the financial risk associated with IPM failure is not large. The majority of the value of IPM is captured by expected profit maximization and the risk sharing needs of even highly risk averse producers are small.

5.2 Model Specification

5.2.1 General Model Overview

The representative producer modeled here manages a homogeneous unit of land normalized to one acre, all devoted to continuous corn production. The producer derives utility from the profit generated from this land and all other income and wealth is ignored. Producer profit is simply the product of price and yield, minus the costs of production. For simplicity, the price of corn is fixed and the cost of production is the same for all production scenarios and so it is ignored. Two independent sources of randomness make yields stochastic in this model. First, the proportion of yield lost each year due to corn rootworm damage is a function of the observed root rating and lodging, which depend stochastically on the initial larval population. The simplified stochastic dynamic corn rootworm population model presented in chapter 4 determines the initial larval population each year. Second, even if no corn rootworm are present, the pest free yield is stochastic as a result of other factors such as nutrient management, irrigation, weed control, and weather related events. The yield uncertainty due to all these factors is captured in the distribution function of pest free yields and the focus here is on stochastic losses due to corn rootworm damage.

The producer influences the distribution of stochastic losses due to corn rootworm by the application of soil insecticides, which in this model is a discrete choice—the producer either does or does not apply a soil insecticide. This accurately reflects producer practices, since producers who do apply insecticides generally do so at the recommended rates. Some producers do obtain good control with applications of 75% or 50% of the recommended rate (Edwards et al. 1999), but this practice is not modeled here since it is not predominate. Despite the discrete nature of insecticide application, the input choice still remains a continuous variable, since the variable of concern is how frequently soil insecticide is applied. The producer maximizes the expected utility of profit by choosing an economic injury level (EIL), which then determines how often soil insecticides are applied. If the previous summer's observed maximum adult population is above the EIL, then the producer applies insecticide. For the status quo case, the EIL is zero so that insecticides are always applied. The alternative of never applying insecticide implies an EIL of positive infinity, or some value sufficiently high that it is never exceeded.

Table 5.1 summarizes the sequence of events for the three production options. For the status quo production technology, the producer simply applies soil insecticide each year at plant. For both IPM scenarios, the producer observes the maximum adult population each summer and uses this information to decide whether or not to apply a soil insecticide the next year at plant. If this observed maximum population is above the EIL, the producer applies insecticide at plant the following spring. For scenarios with IPM insurance, in years when the adult population does not exceed the EIL, the producer purchases actuarially fair insurance. If the observed root rating and/or lodging exceed the predetermined threshold, this insurance pays an indemnity equal to the expected loss. The profit specification for each production technology are reported in the next sub-section. The distribution functions for the root rating and lodging are conditioned on the initial larval population each year, so they depend on the corn rootworm population model. Figure 5.1 graphically summarizes the corn rootworm population model and how the insurance signals and yield loss are determined in the model. Ovals represent observed variables, while arrows represent the flow of stochastic linkages between variables through conditional density functions.

Table 5.1. Sequence of events for the three corn rootworm production technologies

Year	Status Quo	IPM without Insurance	IPM with Insurance
Previous Year	-	Observe Maximum Adult Population	Observe Maximum Adult Population
Previous Year	-	-	Observe Root Rating and Lodging
Previous Year	Harvest Corn and Determine Profit	Harvest Corn and Determine Profit	Harvest Corn and Determine Profit
Current Year	-	-	Purchase IPM Insurance If Adult Population < EIL
Current Year	Plant Corn, Always Applying Insecticide	Plant Corn, Applying Insecticide If Adult Population ≥ EIL	Plant Corn, Applying Insecticide If Adult Population ≥ EIL
Current Year	-	-	Observe Root Rating and Lodging
Current Year	Harvest Corn and Determine Profit	Harvest Corn and Determine Profit	Harvest Corn and Determine Profit

5.2.2 Profit Specifications and Producer Optimization Programs

5.2.2.1 Status Quo Case

For any particular year t, denote per acre producer profit for the status quo case as π_t^{SQ}, which is determined as follows:

$$\pi_t^{SQ} = py_t^{PF}\left(1 - YL_t\right) - C \tag{5.1}$$

The price of corn is fixed at p = \$2.35 per bushel and C = \$12.00 is the cost of purchasing and applying insecticide. The stochastic pest free yield for any year t is denoted y_t^{PF} and it is distributed according to the beta density function, with parameters α and ω and upper and lower limits. The values of these parameters used for the Monte Carlo simulations for Brookings, SD and Boone, IA are reported in Table 5.2. These are the parameter values used for determining county Revenue Assurance (RA) crop insurance premiums for Brookings

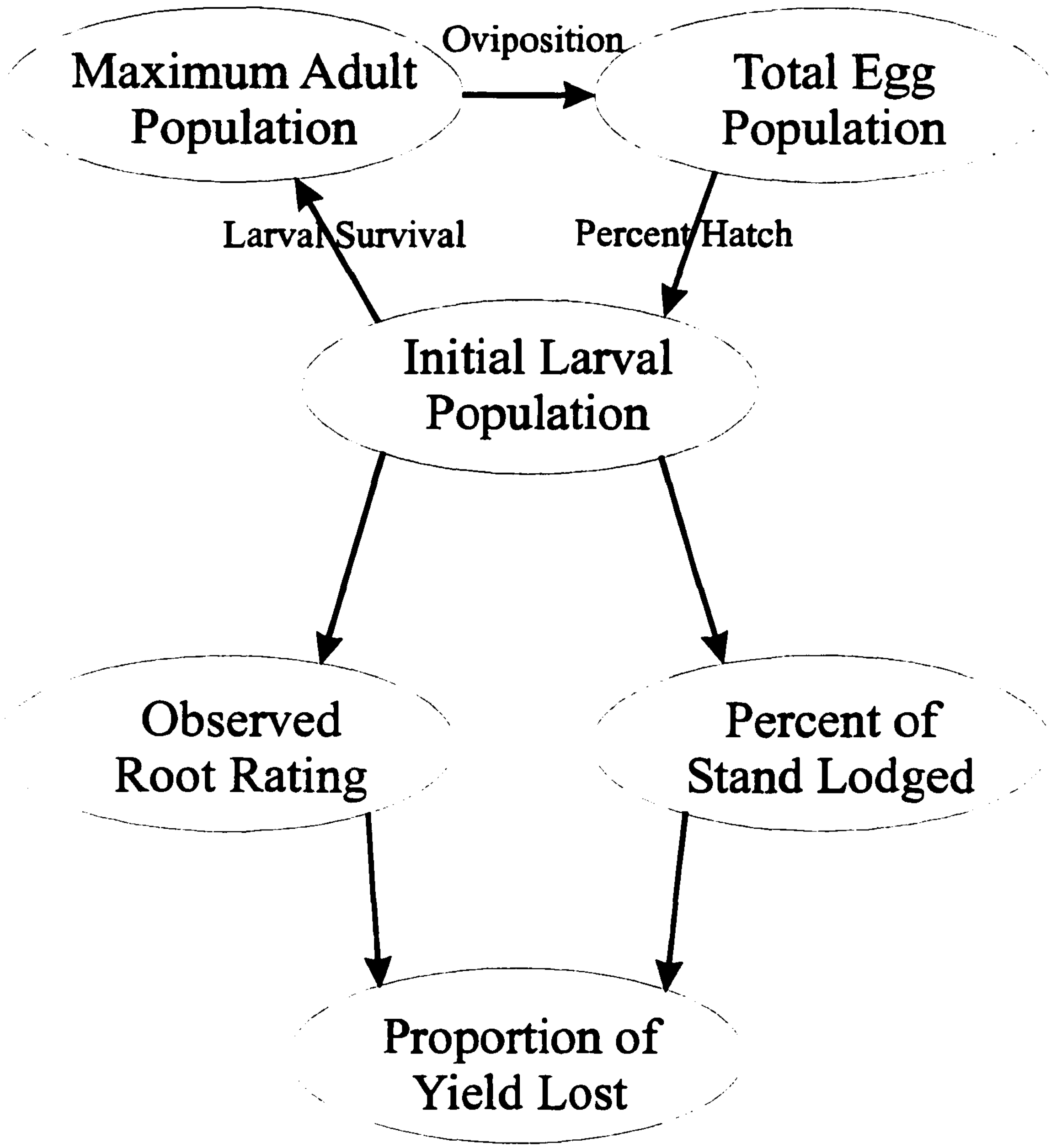


Figure 5.1. Illustration summarizing the stochastic dynamic population model and derivation of root rating, lodging and yield loss from it

Table 5.2. Parameter values for beta density functions for pest free yield

Brookings, SD		Boone, IA	
Parameter	Value	Parameter	Value
α	2.77	α	3.26
ω	1.24	ω	1.61
Lower limit	0.00	Lower limit	0.00
Upper limit	194.10	Upper limit	212.00

County, SD, and Boone County, IA. Irrigated corn is used for Brookings, since typically irrigated corn is planted as continuous corn and regularly treated with soil insecticides. In Boone, dryland corn is used since it predominates among corn cropping systems.

In equation (5.1), YL_t, the stochastic proportion of yield lost in year t due to corn rootworm damage, follows a normal distribution with a mean and standard error depending on the observed root rating and lodging as reported in chapter 4, section 4.3.4. The observed root rating and lodging for any year depend stochastically on the initial larval population as described in chapter 4, sections 4.3.2 and 4.3.3. Specifically, the root rating follows a beta distribution and lodging follows a censored normal distribution, both with their parameters depending on the initial larval population for the particular year. However, the initial larval population each year is determined by the simplified stochastic dynamic corn rootworm population model presented in chapter 4, section 4.2. As a result the distribution function of YL_t is a stochastic process derived from the corn rootworm population model. The producer influences this stochastic process with insecticide applications. Each year an insecticide is applied, the initial larval population is reduced 75%, which is the insecticide efficacy derived in chapter 4, section 4.3.2.2.

Assuming that the distribution of y_t^{PF} captures all uncertainty remaining when all other inputs are used optimally, then the producer does not have an optimization program to implement, because of the ex ante restriction that soil insecticide is applied each year. For the status quo case, the assumption is that it is optimal to apply soil insecticide each year, particularly when no information concerning adult populations has been collected the previous summer. The goal of the empirical analysis is to determine if this is actually optimal, or if collecting information as part of IPM is of value to producers.

The focus here is on the uncertainty in producer returns each year due to corn rootworm damage. As a result, in this evaluation the producer ignores the dynamics of the stochastic corn rootworm damage process, in the sense that no discounting of future utilities is used. The producer acts as if each corn rootworm life cycle is a random event in a purely stochastic process, and so maximizes the expected utility of profit, not the discounted stream of the expected utility of profit. Nevertheless, the corn rootworm population model underlying this process is still maintained as a dynamic stochastic process.

Certainty equivalent returns are used to monetarize producer welfare, which requires determining the expected value of the utility of profit for any year when profit follows the stochastic dynamic process defined by equation (5.1):

$$EU_{SQ} = \frac{1}{N}\sum_{t=0}^{N-1} u(\pi_t^{SQ}) \tag{5.2}$$

where N is the number of years. This expected utility is the long run average utility the producer obtains from this stochastic dynamic production process, assuming no discounting of future expected utilities. Because of the complex nature of the process, analytically determining the expected value is intractable. As a result, the Monte Carlo technique described in section 5.3 is used to estimate the expected value numerically.

5.2.2.2 Integrated Pest Management Case

For any particular year t, denote per acre profit for the IPM scenario as π_t^{IPM}, which is determined as follows:

$$\pi_t^{IPM}(EIL) = py_t^{PF}\left(1 - YL_t(EIL)\right) - D_t(EIL)C \qquad (5.3)$$

All variables have the same definitions as in (5.1) except for D_t, a dummy variable indicating if insecticide is applied in year t, which is determined as follows:

$$D_t(EIL) = \begin{cases} 0 & \text{if } A_{t-1}^{Max} \geq EIL \\ 1 & \text{if } A_{t-1}^{Max} < EIL \end{cases} \qquad (5.4)$$

where A_{t-1}^{Max} is the maximum adult population observed during the previous summer. Again, YL_t is determined as a stochastic function of the observed root rating and lodging in year t, which are stochastic functions of the initial larval population in year t. The stochastic dynamic population model determines the initial larval population each year and the distribution function of YL_t is a stochastic process as in the status quo case. Again, the producer influences this stochastic process with insecticide applications that reduce the initial larval population by 75% in the year they are applied. However, applications do not necessarily occur each year, hence YL_t depends on D_t, which depends on the EIL the producer uses, and we write $YL_t(EIL)$. Lastly, in a manner analogous to the initial larval population, the stochastic dynamic population model determines the maximum adult population each year and as a result the distribution function of A_{t-1}^{Max} is a stochastic process.

For the IPM case, the producer must choose the optimal EIL to use. Again in this evaluation, the producer ignores the dynamics of the process and instead focuses on the uncertainty in profit and how the EIL affects this uncertainty. No discounting is used, so the producer maximizes the expected utility of profit as a function of the EIL:

$$EU_{IPM} = \underset{EIL}{Max}\frac{1}{N}\sum_{t=0}^{N-1} u(\pi_t^{IPM}(EIL)) \tag{5.5}$$

where π_t^{IPM} is defined in equation (5.3) and the stochastic process governing π_t^{IPM} is as described in chapter 4 and this chapter. Because of the complex nature of the stochastic process, analytically deriving the first and second order conditions for this optimization program is intractable. As a result, the Monte Carlo technique described in section 5.3 is used to optimize (5.5) numerically.

5.2.2.3 Integrated Pest Management with Insurance Case

For any particular year t, denote per acre profit for the IPM scenario with green insurance as π_t^{GI}, which is determined as follows:

$$\begin{aligned}\pi_t^{GI}(EIL) = {} & py_t^{PF}(1-YL_t(EIL)) - D_t(EIL)C \\ & -(1-D_t(EIL))M(R_{TH},L_{TH}) + (1-D_t(EIL))I(R_t,L_t,R_{TH},L_{TH})\end{aligned} \tag{5.6}$$

Variables have the same definitions as in (5.3). The added terms are for the actuarially fair premium $M(R_{TH},L_{TH})$ and the insurance indemnity $I(R_t,L_t,R_{TH},L_{TH})$, which only matter when no insecticide is applied ($D_t = 0$). R_{TH} and L_{TH} are the thresholds for the root rating and lodging respectively at which insurance indemnities begin to be paid, such that no indemnity is paid unless the observed root rating and/or lodging are greater than or equal to their respective thresholds. Intuitively, as the thresholds are reduced, the likelihood and magnitude of the indemnity increases, as does the premium. Again, R_t and L_t are the observed root rating and lodging in year t and are the signals used to pay indemnities, analogous to the insurance signal s in chapter 2.

Because both the root rating and lodging are available as insurance signals, three different indemnity schedules are possible—one based on only the observed root rating, one based on only the observed lodging and one based on both the root rating and lodging. The performance of each signal is reported as part of the empirical evaluation of IPM insurance in section 5.5. Each pays producers the value of the expected loss for the observed signal. The specific forms of the indemnity schedules are:

$$I(R_t, R_{TH}) = \begin{cases} 0 & \text{if } R_t < R_{TH} \\ py_t^{PF} m_{RR}(R_t - 1) & \text{if } R_t \geq R_{TH} \end{cases} \tag{5.7a}$$

$$I(L_t, L_{TH}) = \begin{cases} 0 & \text{if } L_t < L_{TH} \\ py_t^{PF} m_{LL} L_t & \text{if } L_t \geq L_{TH} \end{cases} \tag{5.7b}$$

$$I(R_t, L_t, R_{TH}, L_{TH}) = \begin{cases} 0 & \text{if } R_t < R_{TH} \text{ and } L_t < L_{TH} \\ py_t^{PF} m_R(R_t - 1) + m_L L_t & \text{if } R_t \geq R_{TH} \text{ or } L_t \geq L_{TH} \end{cases} \tag{5.7c}$$

Parameter values are from Table 4.7 and m_{RR} denotes m_R when $m_L = 0$, while m_{LL} denotes m_L when $m_R = 0$. The actuarially fair premium for each schedule is the expected value of the respective indemnity. Again, analytically determining this expected value is intractable, so the Monte Carlo integration technique described in the next section is used to determine the fair premium numerically.

The indemnity schedules in (5.7) do not require producers to pay a deductible. When the signal is below the threshold, producers on average sustain small losses not covered by the insurance, but once the signal threshold has been reached they have complete coverage and they receive indemnities equal to their expected losses. For example, if the realized root rating is 4.0, but the root rating threshold is 5.0, the producer receives no indemnity, but on average has a yield loss. Using the coefficients in Table 4.7 for yield loss based only on root rating, the expected yield loss associated with a root rating of 4.0 is 4.0%. Including a deductible in the indemnity schedules reduces the actuarially fair premium and affects welfare gains associated with insurance coverage. Additional analysis not reported here indicated that the welfare gain associated with IPM insurance coverage is reduced by including a deductible. The results reported in this chapter do not include a deducible and so are biased in favor of IPM insurance.

As for the IPM case, the producer must choose the optimal EIL to use. Again in this evaluation, the producer ignores the dynamics of the process and does not discount future utilities. Instead the producer focuses on the uncertainty in profit and how the EIL affects this uncertainty, and so maximizes the expected utility of profit as a function of the EIL:

$$EU_{GI} = \underset{EIL}{Max}\frac{1}{N}\sum_{t=0}^{N-1}u(\pi_t^{GI}(EIL)) \tag{5.8}$$

where π_t^{GI} is defined in equation (5.6) and the stochastic process governing π_t^{GI} is as described in chapter 4 and this chapter. Again the optimization problem is analytically intractable and the Monte Carlo technique described in section 5.3 is used to optimize (5.8) numerically.

5.2.2.4 Similarity of the Corn Rootworm Model and the General Theoretical Model

The production process for the corn rootworm model has the same essential core as the more general stochastic production model developed in chapter 2. As a reminder, in that model the producer chooses the optimal level of the input x with a production function $f(x, \theta, \varepsilon)$, where θ is a potentially observable stochastic input and ε a random production shock. Green insurance coverage required an actuarially fair premium of $M(\beta)$ and paid indemnities $I(s,\beta)$, where β is an index of insurance coverage and s the insurance signal.

In the corn rootworm model, the EIL is similar to x in that as the EIL is increased, the use of the soil insecticide input decreases and vice versa. The analogy holds if x is defined as the negative (or inverse) of the EIL. Similarly, the proportion of yield saved from corn rootworm damage, $(1 - YL_t(EIL))$, is analogous to $f(x, \theta, \varepsilon)$, where $x = -EIL$, A_{t-1}^{Max} is analogous to θ, and ε is a random production shock not affected by x or correlated with θ. To see this, note that the distribution function of YL_t is normal with a mean and standard error that are linear function of the observed root rating (R_t) and lodging (L_t) in year t, as presented in chapter 4, section 4.3.4. This can be expressed as $YL_t = \phi_1(R_t, L_t) + \phi_2(R_t, L_t)\eta$, where ϕ_1 and ϕ_2 are linear functions and η is a normal random variable with a mean of zero and a variance of one. The root rating and lodging depend stochastically on the EIL and A_{t-1}^{Max}, which are analogous to x and θ, and η is analogous to ε if ε is defined as $-\eta$. Lastly, the fixed price p is a multiplicative constant that has no effect and the pest free yield y_t^{PF} is an additional source of uncertainty specific to the corn rootworm model that does not change the qualitative results.

For corn rootworm IPM insurance, either of the thresholds R_{TH} and L_{TH} are analogous to the level of coverage β in chapter 2, once β is appropriately defined. For example, $\beta = 9 - R_{TH}$ or $\beta = 9/R_{TH}$ imply that as the threshold is reduced, β increases, which preserves the maintained assumption that as β increases, the indemnity and the premium increase ($I_\beta > 0$, $M_\beta > 0$). A similar definition of β in terms of L_{TH} is possible.

5.3 Overview of the Monte Carlo Technique

5.3.1 Monte Carlo Analysis

In empirical studies, analytically evaluating integrals composed of nonlinear functions of random variables from distributions such as the gamma or beta can quickly become intractable. Monte Carlo methods are a way to numerically approximate the value of these integrals for the specific functions and parameterizations of the distributions. For the empirical analyses of corn rootworm IPM, Monte Carlo integration is used to evaluate the expected utility of profit as a nonlinear function of several random variables. The essential idea is to draw the needed random deviates from the appropriately parameterized distributions, then to calculate the utility of profit for these specific realizations of the random deviates. Monte Carlo integration then notes that the average of all realizations is an unbiased and consistent estimator of the expected utility of profit (Greene 1997). Increasing the number of iterations reduces the variance of this estimator, so that a sufficiently large number of iterations reduces the error until it is insignificant. A grid search then identifies the EIL that maximizes the expected utility of profit as estimated via Monte Carlo integration.

For the corn rootworm IPM model, this Monte Carlo technique is used for all empirical analyses. The CARA utility function, $u(\pi) = 1 - \exp(-R_A\pi)$, and the profit specifications in (5.1), (5.3) and (5.6) are used as appropriate to evaluate (5.2) and to optimize (5.5) and (5.8). Values of R_A were chosen according to the method of Babcock et al. (1993) so that the risk premium was 20% and 40% of the standard deviation of profit. Table 5.3 summarizes the values of R_A used. The simplified stochastic dynamic population model and the derived damage model described in chapter 4 are used for all analyses. The

Table 5.3. Coefficient of absolute risk aversion values used for Monte Carlo simulations

Location	Risk Premium (as % standard deviation of profit)	Corn rootworm risk only[a]	All variables stochastic[b]
Brookings	20%	0.0169	0.0042
Brookings	40%	0.0371	0.0093
Boone	20%	0.0186	0.0041
Boone	40%	0.0408	0.0091

[a] Pest free yield fixed at its mean in profit specification
[b] All variables stochastic in profit specifications

population model is initialized with a population of 1,000 eggs and run for 100,000 years, for both Brookings, SD and Boone, IA. The grid search for the optimal EIL ranged between 0 and 100 with a step size of 0.5. Sensitivity analysis is used to identify the effect of important parameters such as the plant day and the coefficient of risk aversion. Lastly, the sign and magnitude of various derivatives, such as for the wealth and risk effects, are numerically estimated by changing the value of the requisite parameter and noting the change. Other researchers have used a similar approach to analyze crop insurance and other government support programs and their effects on optimal input use (Ramaswami 1993, Babcock and Hennessy 1996, Hennessy, Babcock and Hayes 1996, Hennessy 1998).

5.3.2 Random Number Generation in C++

The generation of reliable random numbers using computers is an essential part of Monte Carlo analysis, but is not a simple process. Press et al. (1992) expressly warn researchers from using random numbers supplied by software systems, since the series of numbers eventually repeat themselves, which becomes a real concern when drawing numerous random variates as part of a Monte Carlo analysis. In the next sub-sections, the algorithm for generating random variates from specific distributions used in the Monte Carlo analysis or modeling is described.

Using a good generator for uniform random variates is especially important, since the generation of variates from other distributions typically requires uniform random variates. To generate uniform random variates, the algorithm provided by Press et al. (1992) for L'Ecuyer's long-period generator with a Bays-Durham shuffle is used. The algorithm is lengthy to present and more detailed than required for the purposes here. The interested reader should consult Press et al.

Exponential random variates are generated by transforming uniform random variates following Evans et al. (1993): $E(\lambda) = -\frac{1}{\lambda}\ln(U(0,1))$, where $E(\lambda)$ is an exponential random variate with parameter λ and $U(0,1)$ is a uniform random variate between zero and one. To obtain standard normal random variates, the method of transforming uniform random variates presented by Press et al. (1992) is used. Denote two independent uniform random variates between zero and one as U_1 and U_2 respectively. Two independent standard normal random variates are obtained as follows: $N(0,1) = \sqrt{-2\ln(U_1)}\sin(2\pi U_2)$ and $N(0,1) = \sqrt{-2\ln(U_2)}\cos(2\pi U_1)$. However, the algorithm of Press et al. transforms the uniform random variates from the unit square to a point on the unit circle, then uses the sum of their squares and their angle as the uniform random variates, creating a faster algorithm since trigonometric functions are not used. To obtain non-standard normal random variates, standard normal random variates are transformed by multiplying by the desired standard deviation and adding the desired mean.

Following the algorithms presented by Cheng (1998) for Generators 1 and 2, two parameter gamma random variates are generated using the acceptance-rejection method. These algorithms are long and more detailed than necessary for the purposes here. The interested reader should consult Cheng. The method of Cheng is also used to obtain beta random variates by transforming two independent gamma random variates. Let g_1 denote a gamma random variate with parameters k and α and g_2 a gamma random variate with parameters k and ω. Then $b = \dfrac{g_1}{g_1 + g_2}$ is a beta random variate with parameters α and ω.

5.4 Analysis of IPM

5.4.1 Willingness to Pay for IPM

5.4.1.1 Introduction

Risk neutral producers maximize expected profit, so the difference between expected profit for two different production practices measures the willingness to pay to switch practices. Formally, if $E\pi_i$ denotes the expected profit for production practice i, then the willingness to pay (WTP) to switch from practice i to j is $WTP_{i,j} = E\pi_j - E\pi_i$. Risk averse producers maximize expected utility and certainty equivalent returns (CER) convert the expected utility of stochastic profit to a monetary value. Thus the difference between CER for two different production practices measures the willingness to pay to switch practices. For the CARA utility function, if the expected utility for production scenario i is denoted Eu_i, then $CER_i = \dfrac{\ln(1 - Eu_i)}{-R_A}$. Then the willingness to pay to switch from practice i to practice j is $WTP_{i,j} = CER_j - CER_i$.

The willingness to pay is used to measure the value of IPM to producers relative to the status quo practice of annually applying soil insecticides. To determine the adoption incentives provided by IPM, this willingness to pay is then compared to estimates of the cost of implementing IPM. In general the empirical results indicate that both risk neutral and risk averse producers have sufficient adoption incentives to more than cover the cost of implementing IPM. The empirical analysis also indicates that most of the value of corn rootworm IPM is due to the concavity of profit in corn rootworm uncertainty, not due to the concavity of utility in profit. As a result, risk averse producers have only slightly greater willingness to pay for IPM than risk neutral producers. What follows is first a presentation of empirical results for risk neutral producers, then the results for risk averse producers.

5.4.1.2 Risk Neutral Producer's Willingness to Pay for IPM

Figure 5.2 graphically illustrate how expected profit changes as the EIL is increased from 0 to 100. The plot for Brookings is for corn planted on May 14 (Julian day 134) and the plot for Boone is for corn planted on April 29 (Julian day 119). The most striking difference between the curves is their shape. The curve for Brookings is much flatter around the optimal EIL than the curve for Boone. This implies that erroneously using an EIL that is slightly too high or too low has a lower cost in Brookings than in Boone.

The status quo production practice of applying insecticide each year implies an EIL of 0, so that the intercept in each plot is the expected profit for the status quo practice. On the other hand, never applying insecticides implies an EIL of positive infinity and the expected profit at the EIL of 100 approximates this management practice. For Brookings this is the case exactly, but for Boone, the EIL of 100 still implies an insecticide application on average once every five years. For economic analysis, the difference between the expected profit at the

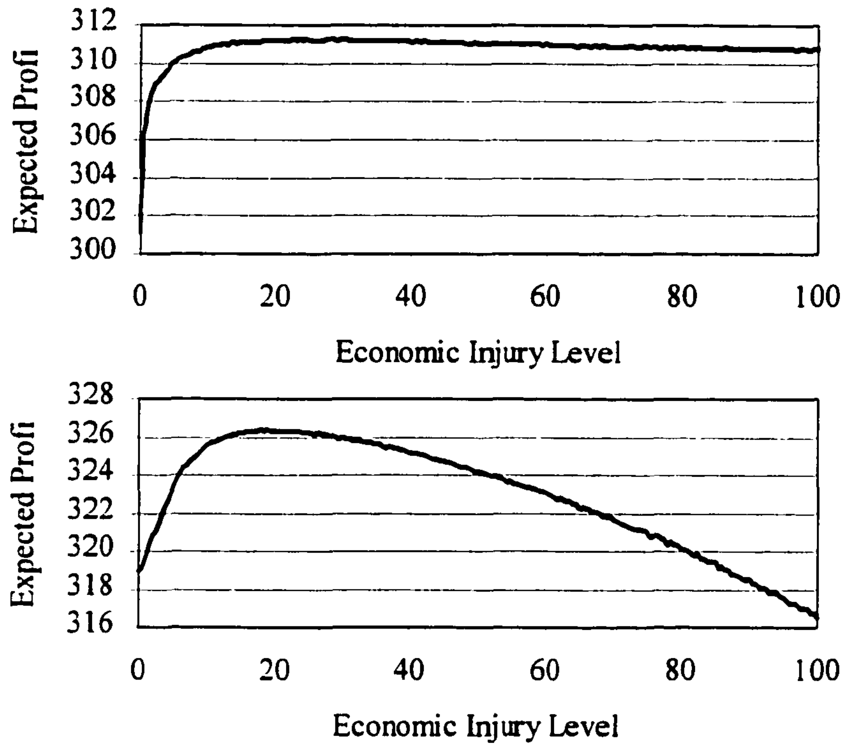


Figure 5.2. Expected profit ($/ac) versus the economic injury level (adults/m^2) for Brookings (top) and Boone (bottom)

maximum and the left intercept for an EIL of 0 is the risk neutral producer's willingness to pay to switch from the status quo practice of always applying insecticide. This willingness to pay is substantial for both locations. On the other hand, the difference between the expected profit at the maximum and the expected profit for an EIL of 100 is the risk neutral producer's willingness to pay to switch from not managing corn rootworm with soil insecticides to using IPM and soil insecticides. For Brookings this is insignificant, but substantial for Boone, as the shape of the curves indicates.

At the expected profit maximizing point on each curve the expected per acre profit is $311.44 in Brookings and $326.52 in Boone, while the associated profits for the status quo practice of annually applying insecticide are $301.37 and $319.10 respectively. (Note that these profit figures do not include typical costs of production such as machinery, harvest and input costs, and so are relatively high. These costs are assumed to be constant across corn rootworm practices and so are ignored.) Thus relative to always applying soil insecticides, a risk neutral producer's per acre willingness to pay for corn rootworm IPM is $10.07 in Brookings and $7.42 in Boone. Repeating this calculation for other plant days yields the data reported in Table 5.4, while Figure 5.3 graphically illustrate how the willingness to pay changes in both locations as the plant day is changed and the optimal EIL for each plant day is used.

The value of IPM relative to the status quo practice of always applying insecticides is greatest when IPM requires the least number of applications. Both practices generally achieve similar levels of corn rootworm control, but IPM generates greater cost savings when it achieves this control with fewer applications, as is the case for Brookings relative to Boone. Thus the willingness to pay is greater in Brookings than in Boone. For both locations, the willingness to pay decreases as the plant day increases. The corn rootworm population does better with later planted corn because adults are better able to coordinate

Table 5.4. Risk neutral producer's willingness to pay ($/ac) for IPM relative to always applying insecticide in Brookings and Boone over a range of plant days

---------- Brookings ----------		---------- Boone ----------	
Plant Day	Willingness to Pay	Plant Day	Willingness to Pay
April 23 (113)	11.79	April 15 (105)	10.17
April 30 (120)	11.52	April 22 (112)	8.86
May 7 (127)	10.97	April 29 (119)	7.44
May 14 (134)	10.08	May 6 (126)	5.82
May 21 (141)	8.88	May 13 (133)	3.96
Average	9.98		7.25

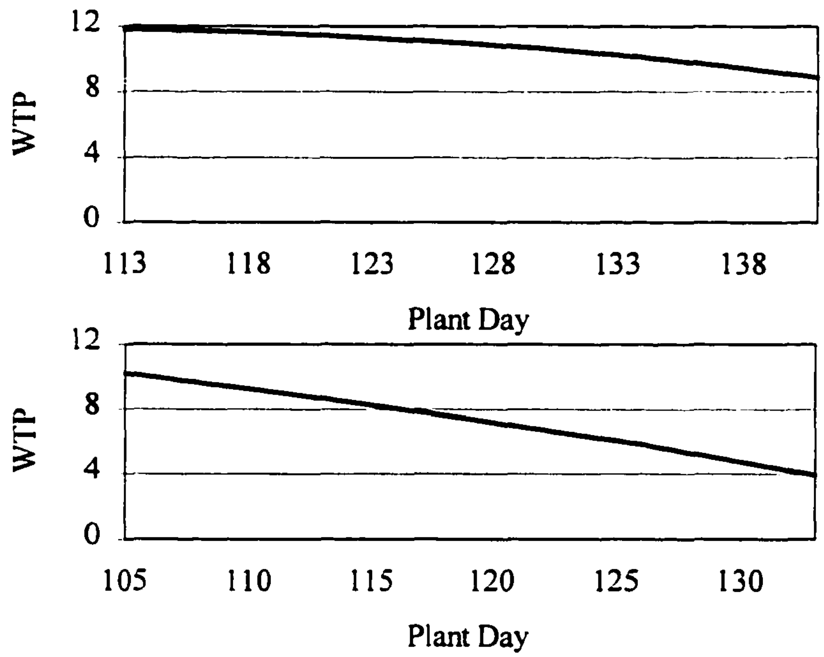


Figure 5.3. Risk neutral producer's willingness to pay ($/ac) relative to always applying insecticide versus plant day for Brookings (top) and Boone (bottom)

their emergence with the period of peak corn flowering, and emerge when their food supply is better. As a result, more adults survive to maturity and each surviving female lays more eggs. Thus the likelihood of observing adults greater than the EIL increases and IPM (correctly) recommends more insecticide applications than for earlier planted corn. The data also show that, for the same plant date, the willingness to pay for IPM is greater in Brookings than in Boone. This occurs because the generally warmer temperatures in Boone are more conducive to corn rootworm growth, and as a result, IPM (correctly) recommends more frequent application of soil insecticides.

The difference between the expected profit at an EIL of 0 and 100 gives the value to risk neutral producers of always using soil insecticide applications and never using them.

Figure 5.2 indicates that for Brookings, producers prefer never applying insecticides to always doing so, and that the added value of IPM is relatively minor compared to never applying insecticide. Nevertheless, annual applications of soil insecticides are still common in the Brookings area, particularly for irrigated corn. On the other hand, for Boone, noting that an EIL of 100 still implies approximately a 20% probability of applying an insecticide, always applying soil insecticide outperforms never applying insecticide. This occurs because the generally warmer climate in Boone is more conducive to corn rootworm growth and economic losses are more likely.

5.4.1.3 Risk Averse Producer's Willingness to Pay for IPM

The primary result thus far is that risk neutral producers have substantial incentives to adopt IPM. However, the typical assumption with intuitive appeal is that producers have some aversion to risk. When producers are risk averse, certainty equivalent returns are the money metric that measures producer welfare, just as expected profit does for the risk neutral producer. Figure 5.4 graphically illustrates how certainty equivalent returns change as the EIL is increased from 0 to 100. Just as for expected profit, the plot for Brookings is for a May 14 (Julian day 134) plant date, while the plot for Boone is for an April 29 (Julian day 119) plant date. Both plots are for a moderate level of risk aversion—a risk premium that is 20% of the standard deviation of profit as reported in Table 5.3. Both curves are shifted downward by the amount of the risk premium, but have essentially the same shape as for expected profit in Figure 5.2, just shifted slightly to the right. The economic implications of this slight shift are discussed in the next sub-section on optimal input use.

To determine how risk aversion affects the value of IPM, the willingness to pay to switch from the status quo practice to IPM is used. This willingness to pay is simply the

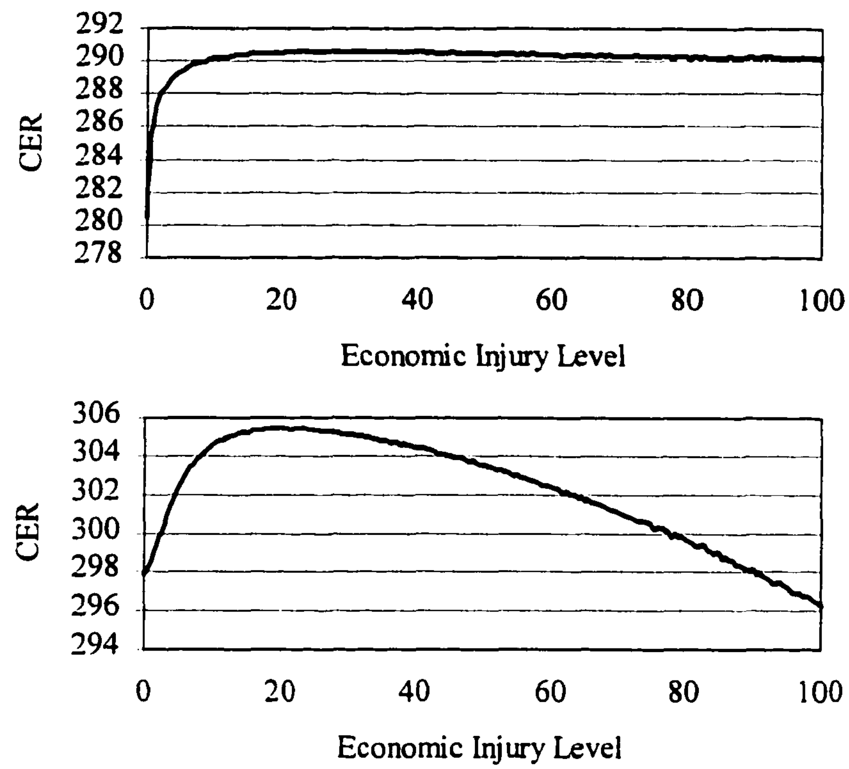


Figure 5.4. Moderately risk averse producer's certainty equivalent returns ($/ac) versus economic injury level (adults/m^2) for Brookings (top) and Boone (bottom)

difference between certainty equivalent returns for both cases. Table 5.5 reports this willingness to pay for moderate and high levels of risk aversion. Figure 5.5 illustrates how this willingness to pay changes in both locations as the plant day increases and the optimal EIL for each plant day is used. When compared to the willingness to pay of risk neutral producers (Table 5.4), these data indicate that accounting for risk aversion increases the value of IPM to producers, but not very much. In terms of Proposition 1 from chapter 2, this implies a slight increase in the incentive to adopt IPM when risk aversion is included in the analysis, while the cost of using IPM remains unchanged.

Table 5.5. Risk averse producer's willingness to pay ($/ac) for IPM relative to always applying insecticide in Brookings and Boone over a range of plant days

Location	Plant Day	Willingness to Pay Moderately Risk Averse[a]	Willingness to Pay Highly Risk Averse[b]
Brookings	April 23 (113)	11.80	11.83
Brookings	April 30 (120)	11.55	11.61
Brookings	May 7 (127)	11.02	11.13
Brookings	May 14 (134)	10.12	10.27
Brookings	May 21 (141)	8.93	9.07
	Average	10.02	10.16
Boone	April 15 (105)	10.28	10.49
Boone	April 22 (112)	9.00	9.21
Boone	April 29 (119)	7.52	7.81
Boone	May 6 (126)	5.91	6.13
Boone	May 13 (133)	4.06	4.24
	Average	7.35	7.58

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

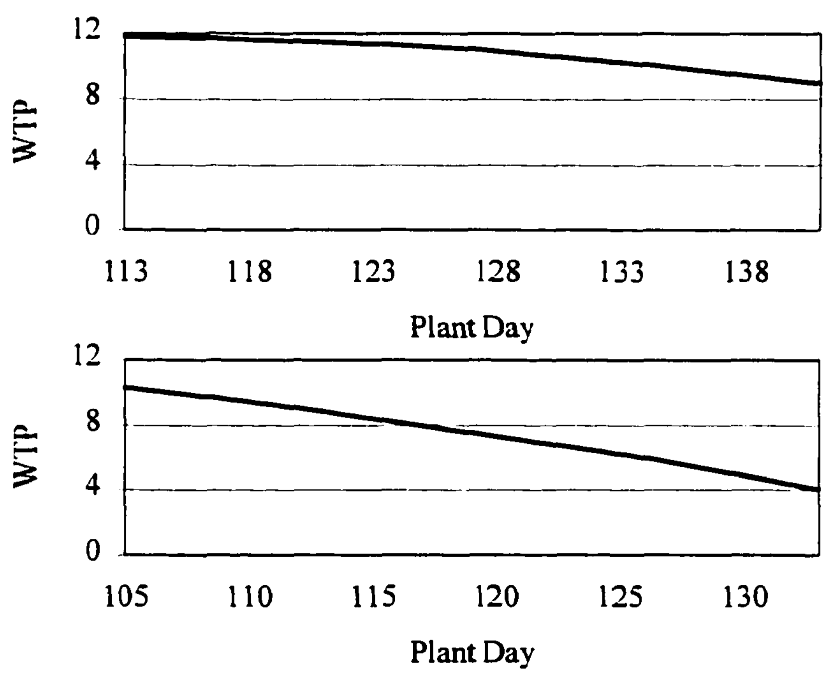


Figure 5.5. Moderately risk averse producer's willingness to pay ($/ac) versus plant day for Brookings (top) and Boone (bottom)

Table 5.4 reports a risk neutral producer's willingness to pay, while Table 5.5 reports a risk averse producer's willingness to pay. The ratio of the risk neutral willingness to pay to the risk averse willingness to pay is the proportion of the total willingness to pay that is due to risk neutrality. These proportions are converted to percentages and reported in Table 5.6 for Brookings and Boone over a range of plant days. This disaggregation of the total willingness to pay is analogous to the analysis of Babcock and Shogren (1995) concerning the willingness to pay for information that eliminates nitrogen input uncertainty in corn production. In their terminology, the proportion of the willingness to pay that is attributed solely to risk neutrality is the production premium, since it is due to the nonlinearity of the production function (and thus producer profit) in the stochastic inputs and does not depend on producer preferences. The percentage due to risk aversion is the risk aversion premium.

Table 5.6. Disaggregation of total willingness to pay into the production premium and the risk aversion premium, expressed as a percentage of the total willingness to pay

		Moderately Risk Averse[a]		Highly Risk Averse[b]	
Location	Plant Day	Production Premium	Risk Aversion Premium	Production Premium	Risk Aversion Premium
Brookings	April 23 (113)	99.9	0.1	99.7	0.3
Brookings	April 30 (120)	99.7	0.3	99.2	0.8
Brookings	May 7 (127)	99.5	0.5	98.6	1.4
Brookings	May 14 (134)	99.6	0.4	98.1	1.9
Brookings	May 21 (141)	99.4	0.6	97.9	2.1
	Average	99.5	0.5	98.2	1.8
Boone	April 15 (105)	98.9	1.1	96.9	3.1
Boone	April 22 (112)	98.4	1.6	96.2	3.8
Boone	April 29 (119)	98.9	1.1	95.3	4.7
Boone	May 6 (126)	98.5	1.5	94.9	5.1
Boone	May 13 (133)	97.5	2.5	93.4	6.6
	Average	98.5	1.5	95.4	4.6

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

and is due to the nonlinearity of utility in stochastic profit. In their analysis, all uncertainty was eliminated by the information technology, while here IPM does not resolve all uncertainty. Later analysis removes all uncertainty, but this does not change the essential result found here—as the data in Table 5.6 indicate, the production premium accounts for the majority of the willingness to pay for IPM. The economic implications of this result for IPM insurance are addressed in section 5.5.

5.4.1.4 Cost of Implementing IPM

The primary cost of IPM is scouting for insects during the appropriate time. Producers can do this themselves and Foster et al. (1986) estimate $0.44 per acre for Iowa to scout just corn rootworm. However, most producers using IPM do not scout themselves, but typically hire crop consultants to do regular scouting throughout the season and then to provide various management recommendations, including insect management. The costs of this service vary, depending on the region and the specific services included in the contract. The typical range is from $5-$8 per acre, but this includes all services, not just corn rootworm scouting. For example, Gerber et al. (1999) report a cost of $6.50 per acre in Indiana for hiring a full service crop consultant, which includes recommendations for tillage and rotations, nutrient management, weed control and management of pertinent insect species, including corn rootworm. Thus $5 per acre is an estimate of the cost for a producer not currently using a crop consultant to hire a crop consulting service primarily for corn rootworm IPM. This estimate is used for evaluating the adoption incentives provided by corn rootworm IPM.

Referring to Proposition 1 and Corollaries 1 and 2 in chapter 2, the producer has an incentive to adopt the BMP if the implementation costs do not exceed the value of the technology to the producer. Using a cost of $5 per acre for hiring a crop consultant and the empirical results presented in Table 5.4 and Table 5.5, the benefits generally exceed the costs so that risk neutral and risk averse producers have an incentive to adopt IPM. Only for late planted corn in Boone does the value of IPM fall below the cost of hiring a full service crop consultant. Producers who regularly plant their corn late may find it optimal to always apply soil insecticides and not hire a crop consultant for corn rootworm management recommendations, unless the value of the service in other areas of crop production are sufficient to warrant the cost. If the primary benefit expected is reduced costs for corn rootworm control via IPM, hiring a consultant is not worth the cost for these producers.

5.4.2 Impact of IPM on Optimal Insecticide Use

5.4.2.1 Introduction

Optimal insecticide use changes when producers adopt IPM. In chapter 2, section 4.2.2, this change was referred to as the adoption effect. It was not possible to develop a formal proposition that identified conditions that determine the sign and or magnitude of this adoption effect, rather it remained an empirical issue. In this section the results of the empirical analysis of the adoption effect for corn rootworm IPM are presented, first for a risk neutral producer, then for a risk averse producer.

The data used to generate plots such as reported in Figures 5.2 and 5.4 allow determination of the optimal EIL—the EIL associated with the maximum expected profit or certainty equivalent returns is the optimal EIL for the specific parameters. As part of the Monte Carlo simulations, the frequency of insecticide application is calculated for each EIL, then this frequency is converted to a percent. For the status quo practice, the EIL is 0 and insecticide is applied 100% of the years. As the EIL increases from 0, the percent of years that insecticide is applied decreases. This percent indicates of how the long run average rate of insecticide use for a producer adopting IPM with this EIL compares to the status quo practice. Alternatively, the measure indicates how the annual average rate of insecticide use in a region changes due to regional adoption of IPM.

5.4.2.2 The Adoption Effect for Risk Neutral Producers

Table 5.7 reports the optimal EIL and associated percent of years that soil insecticide is applied for risk neutral producers in each location over a range of plant days. The data indicate that adopting IPM reduces insecticide in both locations and for all plant days. The adoption effect for risk neutral producers is substantial, implying a reduction in the optimal application rate ranging from 50% to 100%, depending on the location and plant day.

The optimal rate increases for later planted corn because adults are better able to coordinate their emergence with the period of peak corn flowering and emerge when their food supply is better. The overall population is greater, since more adults survive and each surviving female lays more eggs, so that more control is required to prevent economic losses.

Table 5.7. Risk neutral producer's optimal EIL and insecticide application rate expressed as a percent of the status quo rate for Brookings and Boone for a range of plant days

--------------- Brookings ---------------			--------------- Boone ---------------		
Plant Day	Optimal EIL[a]	%	Plant Day	Optimal EIL	%
April 23 (113)	100.0	0.0	April 15 (105)	32.0	2.0
April 30 (120)	100.0	0.0	April 22 (112)	24.5	10.2
May 7 (127)	42.0	1.6	April 29 (119)	19.0	21.7
May 14 (134)	26.0	7.7	May 6 (126)	16.5	34.4
May 21 (141)	21.0	15.8	May 13 (133)	13.0	50.3
Average	57.8	5.0		21.0	23.7

[a] An optimal EIL of 100 implies an EIL sufficiently high that soil insecticide is never applied.

The optimal application rate is also higher for Boone than for Brookings because the climate in Boone is generally more conducive to corn rootworm growth, so that again more control is required to prevent economic losses. Indeed, the climate in Brookings is such that it is never optimal to apply insecticide on corn that is regularly planted early, since the population pressure is never sufficient to warrant the cost of insecticide application.

The typical EIL recommended for use by entomologists is one adult per plant. The EIL reported here are adults per square meter and must be converted to a per plant basis for comparison. Following Stamm et al. (1985), a typical plant density of 70,000 plants per hectare (28,330 plants per acre) implies that dividing adults per square meter by seven gives adults per plant. Thus, when converted to a per plant basis, the optimal economic injury levels reported in Table 5.8 range from three to positive infinity for Brookings and approximately two to five for Boone. Several explanations for the difference between these optimal EILs and the recommended EIL are possible. First, the population and damage models developed in chapters 3 and 4 may not be accurate. Alternatively, note that the population model used here is for the northern corn rootworm only. However, the western corn rootworm also causes significant yield losses. If both species were included in the model with competition between them, the optimal EIL for the total number of corn rootworm observed (northern plus western) probably would be lower. Lastly, maybe the recommended EIL is not expected profit or utility maximizing.

Foster et al. (1986, p. 304) note that the recommended EIL has been developed "...based on many years of experience rather than experimental data." Indeed, Foster et al. use Bayesian analysis of field data from Iowa and find that the value of corn rootworm

Table 5.8. Risk averse producer's optimal insecticide application rate expressed as an EIL and as a percentage of the status quo rate

		Moderately Risk Averse[a]		Highly Risk Averse[b]	
Location	Plant Day	Optimal EIL[c]	%	Optimal EIL[c]	%
Brookings	April 23 (113)	100.0	0.0	100.0	0.0
Brookings	April 30 (120)	100.0	0.0	100.0	0.0
Brookings	May 7 (127)	45.5	1.4	51.0	1.1
Brookings	May 14 (134)	28.0	7.1	29.5	6.8
Brookings	May 21 (141)	23.0	15.1	25.5	14.3
	Average	59.3	4.7	61.2	4.4
Boone	April 15 (105)	34.0	1.7	34.5	1.6
Boone	April 22 (112)	24.5	9.7	25.5	9.2
Boone	April 29 (119)	21.0	20.3	23.0	18.9
Boone	May 6 (126)	18.0	32.9	19.5	31.3
Boone	May 13 (133)	13.5	49.5	15.0	47.7
	Average	22.2	22.8	23.5	21.7

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.
[c] An optimal EIL of 100 implies an EIL sufficiently high that soil insecticide is never applied.

scouting information is zero, so that the recommended corn rootworm management practice in Iowa is to always apply insecticide. Naranjo and Sawyer (1989b) use their simulation model developed from field data from New York to derive the optimal EIL and the impact of planting date, peak flower, and temperature. They do not report the actual EILs, but normalize them to the recommended EIL for a "typical" year and field. Their figures are difficult to read, but the optimal normalized EIL varies between approximately one fourth and five times the recommended EIL. Stamm et al. (1985) analyze field data from Nebraska and find that using an EIL of 0.75 increases IPM prediction accuracy to greater than 90%. Thus it is difficult to find conclusive experimental and/or theoretical support for the recommended EIL and reconciling the differing results requires additional research.

Further analysis of the work of Stamm et al. and Foster et al. provides insight. First, borrow terminology from statistical decision theory to define type I and type II errors in the context of IPM. A type I error occurs when IPM recommends that no insecticide be applied, but in the ex post analysis, the realized yield loss is sufficiently high that insecticide should have been applied. A type II error occurs when IPM recommends an insecticide application, but in the ex post analysis, the insecticide was unnecessary. In the analysis of Stamm et al., IPM prediction accuracy is measured only as the probability of a type I error and the probability of a type II error is ignored. Indeed, with an EIL of 1.0, they report a probability of 10.9% for a type I error, which is reduced to 3.6% with an EIL of 0.75. However, their data imply a 52% probability of a type II error for an EIL of 1.0, which can only increase when the EIL is reduced. Similarly, the data of Foster et al. indicate no type I errors with an EIL of 1.0 using the 1-9 root rating scale, but a 34.3% probability of a type II error. It seems possible that the recommended EIL has been developed "...based on many years of experience..." to greatly reduce the likelihood that IPM commits a type I error, since such errors would be damaging to the reputation of IPM and reduce producer adoption. A producer can often identify when a type I error has occurred, since lodged corn is easily noticed, as are rootworm feeding scars on corn roots. However, a type II error is difficult to detect, unless the producer plants a test plot to determine if the insecticide application was warranted.

The main point I wish to make is that the optimal economic injury levels identified with the model here are potentially different from the recommended EIL for two reasons. First they were identified in a different manner than used to determine the recommended

EIL. Second, they were chosen with a different objective than seems to be the case for the recommended EIL.

5.4.2.3 The Adoption Effect for Risk Averse Producers

Table 5.8 reports the optimal EIL and associated percent of years that soil insecticide is applied for risk averse producers in each location, over a range of plant days and for two levels of risk aversion. Comparing these results with those in Table 5.7 for the risk neutral producer indicates that as risk aversion increases, the optimal insecticide application rate decreases. Thus, relative to risk neutral producers, risk averse producers do not find it optimal to increase insecticide applications to further reduce the risk of lose from corn rootworm. Rather risk averse producers prefer to increase the EIL to further reduce the risk of expenditures on unnecessary insecticide applications. Thus risk averse producers prefer to reduce the probability of type II IPM errors, not type I. This preference is opposed to the apparent objective used to determine the recommended EIL.

In a manner similar to the willingness to pay for IPM, the adoption effect on optimal input use can be disaggregated into a production effect and a risk aversion effect. In this context, the production effect is the reduction in optimal input use occurring due solely to the nonlinearity of the production function (and thus producer profit) in the stochastic factors, which does not depend on producer preferences. The risk aversion effect is the reduction in optimal input use occurring as a result of the nonlinearity of producer preferences in stochastic profit. The data are not reported, but as with the willingness to pay for IPM, the majority (> 95%) of the adoption effect is due to the production effect and not the risk aversion effect.

5.4.3 Optimal versus Uniform EIL

The previous analysis of IPM assumed that producers used the optimal EIL that varied with the plant day and location. However, typically IPM uses a uniform EIL (e.g. one adult per plant), not an EIL that varies with the plant day and/or location. The simplicity of the uniform EIL is its primary advantage, since the crop consultant and/or producer does not have to worry about other complicating factors when deciding whether to apply insecticide. However, this simplicity has cost associated with it—producers must deviate from the optimal EIL and as a result incur welfare losses. In addition, application rates for soil insecticides are too high in some instances and too low in others, with the net effect on overall insecticide use indeterminate. What follows is an analysis that determines the welfare costs associated with non-optimal EILs and their effect on insecticide use. In general the results indicate that the cost associated with a constant uniform EIL for all plant days and locations is relatively small—on average less than thirty cents per acre—and that the application rate changes very little.

The cost to risk neutral producers of using a uniform EIL for corn rootworm can be determined here as the difference between expected profit with the optimal EIL and expected profit with the uniform EIL for each plant day. For risk averse producers, the cost is the difference between certainty equivalent returns with the optimal EIL and with the uniform EIL. The uniform EIL is varied from 7 to 35 adults per square meter (1 to 5 adults per plant). Table 5.9 reports the cost to a risk neutral producer and Table 5.10 reports the cost for a highly risk averse producer. The costs for a moderately risk averse producer are approximately the average of the costs reported in Tables 5.9 and 5.10.

Table 5.9. Risk neutral producer's cost of using different uniform EILs in Brookings and Boone over a range of plant days

Location	Plant Day	Cost: EIL = 7	EIL = 14	EIL = 21	EIL = 28	EIL = 35
Brookings	April 23 (113)	0.36	0.07	0.02	0.01	0.00
Brookings	April 30 (120)	0.78	0.23	0.09	0.04	0.01
Brookings	May 7 (127)	0.87	0.26	0.10	0.03	0.01
Brookings	May 14 (134)	0.76	0.20	0.06	0.01	0.08
Brookings	May 21 (141)	0.61	0.09	0.00	0.11	0.20
	Average	0.68	0.17	0.05	0.04	0.06
Boone	April 15 (105)	1.73	0.40	0.12	0.03	0.02
Boone	April 22 (112)	2.02	0.37	0.04	0.03	0.22
Boone	April 29 (119)	1.83	0.21	0.03	0.30	0.75
Boone	May 6 (126)	1.29	0.08	0.19	0.79	1.63
Boone	May 13 (133)	0.64	0.01	0.53	1.55	2.77
	Average	1.50	0.21	0.18	0.54	1.08

Table 5.10. Highly risk averse[a] producer's cost of using various uniform EILs for IPM in Brookings and Boone for a range of plant days

Location	Plant Day	Cost: EIL = 7	EIL = 14	EIL = 21	EIL = 28	EIL = 35
Brookings	April 23 (113)	0.37	0.07	0.02	0.01	0.00
Brookings	April 30 (120)	0.86	0.25	0.12	0.04	0.02
Brookings	May 7 (127)	1.03	0.36	0.16	0.07	0.04
Brookings	May 14 (134)	0.98	0.34	0.12	0.03	0.04
Brookings	May 21 (141)	0.80	0.22	0.05	0.09	0.09
	Average	0.81	0.25	0.09	0.05	0.04
Boone	April 15 (105)	1.97	0.53	0.18	0.05	0.01
Boone	April 22 (112)	2.36	0.56	0.07	0.00	0.09
Boone	April 29 (119)	2.25	0.43	0.08	0.19	0.50
Boone	May 6 (126)	1.59	0.20	0.12	0.54	1.19
Boone	May 13 (133)	0.87	0.02	0.24	1.07	2.04
	Average	1.81	0.35	0.14	0.37	0.77

[a] With a 40% risk premium and all variables stochastic. See Table 5.3.

Examining the data in Table 5.9 indicates that in Brookings the cost is relatively high for an EIL that is too low, but the cost is low and fairly unresponsive to an EIL that is too high. On the other hand, in Boone the cost is relatively more expensive overall and this cost increases noticeably in either direction from the optimal EIL. Examining Figure 5.2 explains graphically the data in Table 5.9. The relatively flat curve for Brookings around the maximum indicates a small loss for a non-optimal EIL, whereas the curve for Boone exhibits rapid declines in either direction around the maximum, so that the cost of a non-optimal EIL is higher.

Intuitively, an EIL that is too low implies unnecessary insecticide applications, while an EIL that is too high implies missed opportunities to reduce losses by applying insecticide. Using previously defined terminology, an EIL that is too low implies an increased probability of a type II error and an EIL that is too high implies an increased probability of a type I error. In either location the observed adult population rises above an EIL that is too low sufficiently often that the unnecessary applications reduce the value of IPM. This happens more often in Boone, because the generally warmer conditions are more conducive to corn rootworm growth, so that the cost of unnecessary applications is greater in Boone. Indeed, corn rootworm do so poorly in Brookings that the expected cost of missed opportunities for control are low and only begin to rise for late planted corn. On the other hand, in Boone, the cost of missed opportunities to control corn rootworm is very high, particularly for late planted corn. Lastly, the data in Table 5.9 indicate that the costs of an EIL that is too low are spread fairly evenly among plant days, whereas the costs of an EIL that is too high are primarily concentrated among the late plant days, particularly in Boone.

Table 5.10 reports the cost to a highly risk averse producer (as defined in Table 5.3) associated with using the indicated EILs. The general trend is for the cost to increase for EILs that are too low and to decrease for late plant days and EILs that are too high. For Brookings, the changes are only a few cents and the decrease for late plant days and high EILs only happens for a few cases. However in Boone, the cost to a risk averse producer increases over thirty cents on average for an EIL that is too low, and for EILs that are too high, the cost decreases substantially for producers who regularly plant corn late. These trends in the data in Table 5.10 imply that risk averse producers find unnecessary insecticide applications (type II errors) more costly than risk neutral producers, and find missed opportunities to control corn rootworm (type I errors) less costly than risk neutral producers. This generalization was noted previously in section 5.4.2.3 in the discussion concerning the effect of risk aversion on the optimal EIL.

Considering all the data in Table 5.9, an EIL of 21 minimizes the cost of a uniform EIL. However, minimizing the cost does not imply that expected profit or certainty equivalent returns are maximized. The data are not reported here, however on average across all plant days and locations, a uniform EIL of 21 also maximizes the willingness to pay for IPM relative to always applying insecticide for both risk neutral and risk averse producers. The cost of using this uniform EIL is slight, except for late plant dates in Boone, where it ranges around 50 to 25 cents per acre. Allowing a lower EIL of 14 for this situation would greatly reduce this cost.

When the cost of hiring a crop consultant is included along with the cost of using a uniform EIL of 21, the primary result from section 5.4.1.4 still holds. Using a cost of $5 per acre, the willingness to pay for IPM relative to always applying insecticide still exceeds this cost, except for late planted corn in Boone. A lower uniform EIL of 14 only reduces the loss associated with IPM adoption, and is not sufficient to provide a positive adoption incentive. Producers who regularly plant late corn will not find it optimal to hire a crop consultant to obtain to reduce corn rootworm management costs via IPM, unless the value of the service in other areas of crop production is sufficient.

Besides affecting producer welfare, a uniform EIL affects the application rate of soil insecticides. Tables 5.11 and 5.12 report the application rates associated with different uniform EILs, as well as the optimal rates for risk neutral and risk averse producers for comparison. As expected, as the EIL decreases the rate increases. Also, as the plant day increases, the rate increases because the corn rootworm population does better with late planted corn. and the rate is higher in Boone than in Brookings because the climate in Boone is more conducive to corn rootworm than in Brookings. Using the optimal EIL of 21 in Brookings results in an increase in the application rate over the optimal rate in all cases, but the highest rate is still less than 16% of the status quo rate. However, with an EIL of 21 in Boone, the application rate is greater than the optimal rate for early plant dates and less for late plant dates. The average rate across all plant dates in Boone with the uniform EIL of 21 is slightly less except for highly risk averse producers.

In summary, the welfare costs associated with using a uniform EIL can potentially be substantial for early or late planted corn and relatively low or high EILs. However, the optimal uniform EIL of 21 results in welfare costs that on average are less than 20 cents per acre; only late planted corn in Boone exceeds this average. This small effect does not change the qualitative results presented in previous sections—IPM still has substantial value to producers over the status quo practice, except for producers who regularly plant late corn. In addition, the optimal uniform EIL of 21 results in only a slight increase of the application rate over the optimal rate on Brookings, but on average a slight decrease of the average application rate in Boone. Thus the simplicity and resulting ease in implementation and education created by a uniform EIL do not incur substantial welfare or environmental costs.

Table 5.11. Optimal application rates and application rates for uniform EIL for Brookings expressed as percentage of the status quo rate

	Risk	Risk	Risk	Uniform Economic Injury Level				
Plant Day	Neutral	Averse[a]	Averse[b]	7	14	21	28	35
April 23 (113)	0.0	0.0	0.0	3.2	0.6	0.2	0.1	0.0
April 30 (120)	0.0	0.0	0.0	8.3	3.0	1.5	0.8	0.5
May 7 (127)	1.6	1.4	1.1	13.0	6.7	4.4	3.0	2.2
May 14 (134)	7.7	7.1	6.8	18.9	12.2	9.2	7.1	5.9
May 21 (141)	15.8	15.1	14.3	26.9	19.6	15.8	13.8	11.8
Average	5.0	4.7	4.4	14.1	8.4	6.2	5.0	4.1

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

Table 5.12. Optimal application rates and application rates for uniform EIL for Boone expressed as percentage of the status quo rate

	Risk	Risk	Risk	Uniform Economic Injury Level				
Plant Day	Neutral	Averse[a]	Averse[b]	7	14	21	28	35
April 15 (105)	2.0	1.7	1.6	22.8	8.7	4.3	2.4	1.6
April 22 (112)	10.2	9.7	9.2	37.0	18.2	11.5	8.3	6.9
April 29 (119)	21.7	20.3	18.9	47.8	27.6	20.3	17.0	15.3
May 6 (126)	34.4	32.9	31.3	56.2	37.8	30.7	27.8	26.6
May 13 (133)	50.3	49.5	47.7	64.3	49.0	42.7	40.6	40.1
Average	23.7	22.8	21.7	45.6	28.3	21.9	19.2	18.1

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

5.5 Analysis of IPM Insurance

5.5.1 Willingness to Pay for IPM Insurance

5.5.1.1 Choice of Insurance Signal

The model of corn rootworm IPM insurance developed here has two stochastic variables available for use as insurance signals for paying indemnities—the observed root rating and the percent of the stand lodged. The three insurance schedules reported in equations (5.7a-c) were developed to determine how root rating alone, lodging alone, and root rating and lodging together perform as insurance signals. All three schedules pay producers an indemnity that equals the expected loss associated with the observed signal, but only when the signal is above the threshold. Producers receive this coverage at an actuarially fair premium and the willingness to pay for IPM with this insurance coverage serves as the criterion to determine which signal performed best from the producer's perspective.

As previously noted, producers pay no deductible, which biases the analysis in favor of IPM insurance. For the results reported here, the root rating threshold for indemnities is 5.0 and the lodging threshold is 5%. Using the coefficients reported in Table 4.7, for the indemnity based only on the root rating the threshold value of 5.0 implies an average yield loss of 5.34% before an indemnity is received. For the indemnity based only on lodging the threshold value of 5% implies an average yield loss of 0.69% before an indemnity is received. For the indemnity schedule using both signals, the expected yield loss before an indemnity is received ranges between 0.50% and 2.24%, depending on the exact combination of root rating and lodging that occurs when either threshold is met. These losses at the threshold could be subtracted from the indemnity as deductibles, however, in the results reported here, this is not the case, which biases the analysis in favor of IPM insurance.

These thresholds imply a wide range of expected losses before IPM insurance coverage begins. The threshold root rating of 5.0 was chosen because it roughly corresponds to the threshold used by the corn rootworm IPM insurance developed by IGF Insurance (Griffin 1999). The IGF insurance product uses a root rating threshold of 3.5 on the 1-6 scale, which corresponds to approximately a 6.0 on the 1-9 scale (Oleson 1998). The other two schedules include a high level of coverage and a moderate to high level as alternatives.

Risk neutral producers who maximize expected profit have no incentive to purchase actuarially fair insurance that uses a linear indemnity schedule as the insurance here does. Certainty equivalent returns for a risk averse producer, who purchases IPM insurance whenever IPM recommends that no insecticide be applied, are used to measure producer welfare under IPM insurance coverage. Figure 5.6 illustrates graphically how certainty equivalent returns for a moderately risk averse producer (as defined in Table 5.3) with IPM insurance coverage based on both the root rating and lodging change as the EIL increases from 0 to 100. As for previous plots, the plot for Brookings is for corn planted on May 14 (Julian day 134) and the plot for Boone is for corn planted on April 29 (Julian day 119). In general, no difference between these plots and those in Figure 5.4 is readily noticeable except for a slight vertical shift upward.

To visually compare the three insurance programs, the difference between certainty equivalent returns using IPM with and without each type of insurance are used. This is simply the willingness to pay to switch from using IPM without IPM insurance to using IPM with actuarially fair insurance based on one of the three different signals. Figure 5.7 illustrates how this willingness to pay changes as the EIL increases from 0 to 100.

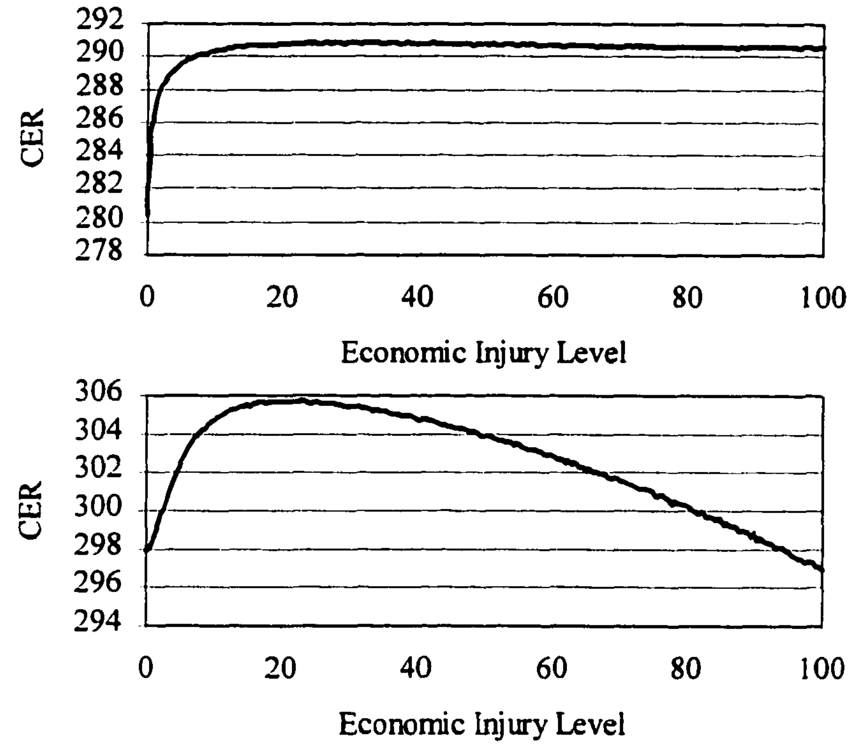


Figure 5.6. Moderately risk averse producer's certainty equivalent returns with IPM insurance paying indemnities based on both the root rating and lodging ($/ac) versus economic injury level (adults/m^2) for Brookings (top) and Boone (bottom)

Clearly as an insurance signal, at the thresholds used, lodging alone outperforms the root rating alone and using both root rating and lodging. This is partly due to the lower indemnity implied by the 5% lodging threshold. However, the low willingness to pay for the root rating threshold was surprising, given that it is similar to that used for the IGF insurance product. To make the IPM insurance as attractive as possible, all analyses of IPM insurance in subsequent sections use only insurance that pays indemnities based on the observed lodging. Lastly, note that the increase of the willingness to pay for IPM insurance as the EIL increases is to be expected, since a higher EIL implies a greater probability of corn rootworm damage.

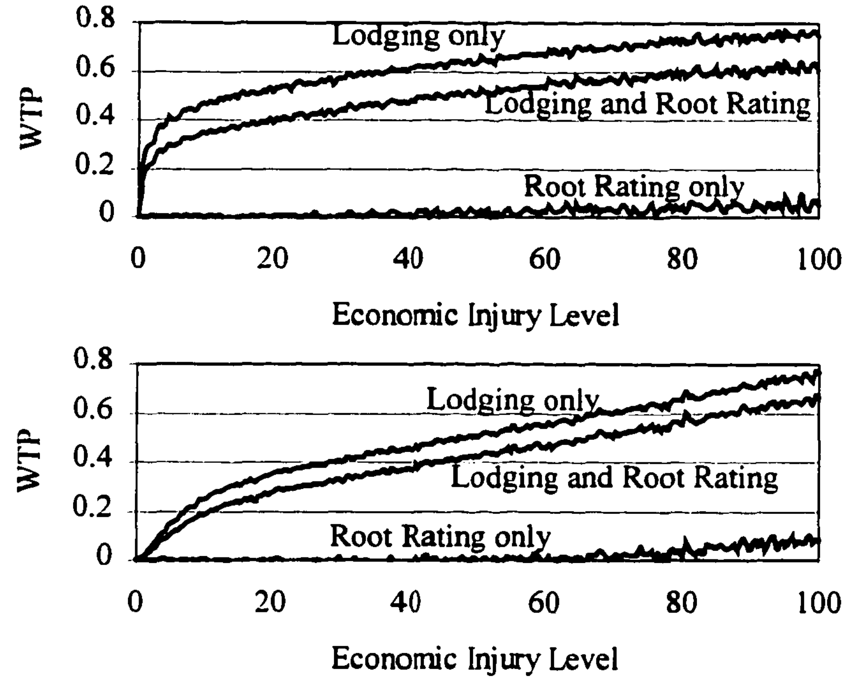


Figure 5.7. Moderately risk averse producer's willingness to pay ($/ac) for IPM insurance versus the economic injury level (adults/m^2) for Brookings (top) and Boone (bottom)

The choice of lodging as an insurance signal has empirical support in the literature. Lodging is an important determinate of yield loss associated with corn root worm damage—observed root ratings can be the same for lodged and unlodged corn, but if plants lodge as a result of corn rootworm feeding, yield losses can be substantial. Spike and Tollefson (1991) used artificial corn rootworm infestations and artificial lodging to experimentally demonstrate that artificially induced lodging caused on average an additional 12% yield loss in artificially infested corn in a wet year. In a dry year, they found no yield difference between corn artificially infested and uninfested, but artificially lodged corn exhibited a 34% yield loss even when no corn rootworm were present. Their results are consistent with the finding here that producers have the greatest willingness to pay for insurance paying indemnities based on lodging.

The low willingness to pay for insurance based on the root rating seems surprising, given the focus in the literature on the root rating as a measure of the effectiveness of control practices at reducing corn rootworm population pressure. However, corn rootworm population pressure, which the root rating measures, and yield loss are two separate, but related variables. Gray and Steffey (1998) conducted an extensive evaluation of root ratings based on a four-year field study in two locations Illinois with twelve different corn varieties. They find that root ratings well below typical thresholds can be associated with economic yield losses. As a result, insecticide applications are profitable even when untreated plots exhibit root ratings that are typically considered indicative of sub-economic damage. This result is consistent with the results of Spike and Tollefson (1991) and the finding here that insurance paying indemnities based on root ratings has low value to producers.

5.5.1.2 Willingness to Pay for IPM Insurance Based on Optimal EIL versus Uniform EIL

In this brief sub-section, the willingness to pay for IPM with insurance coverage when IPM uses the EIL optimal for the specific plant day and location is compared to the willingness to pay for IPM with insurance coverage when IPM uses a uniform EIL for all plant days and locations. Data used to generate figures such as Figure 5.6 were used to determine the certainty equivalent returns associated with the optimal EIL and several other EILs, for each plant day and location, and both levels of risk aversion. Using these certainty equivalent returns data, the willingness to pay for IPM with insurance coverage based on lodging using each EIL, relative to always applying insecticide can be determined. Table

5.13 reports the results for a moderately risk averse producer, while Table 5.14 reports the same results for a highly risk averse producer.

The cost of using each EIL is simply the difference between the willingness to pay for IPM insurance with the optimal EIL (EIL*) and the uniform EIL. Again an EIL of 21 maximizes the average willingness to pay over all plant dates for both regions and as before, the cost associated with this EIL is generally only a few cents. Thus insurance does not change the qualitative result obtained in section 5.4.3—the simplicity and ease of implementation created by a uniform has few associated welfare costs.

5.5.1.3 Evaluation of Corn Rootworm IPM Insurance

Proposition 2 in chapter 2 demonstrated that if the marginal utility of profit and the marginal indemnity for an increase of coverage are positively correlated, then actuarially fair green insurance increases producer incentives for BMP adoption. This proposition follows

Table 5.13. Moderately risk averse[a] producer's willingness to pay ($/ac) for IPM with insurance with different EILs in Brookings and Boone over a range of plant days

		Willingness to Pay					
Location	Plant Day	EIL*	EIL=7	EIL=14	EIL=21	EIL=28	EIL=35
Brookings	April 23 (113)	12.09	11.72	12.02	12.07	12.09	12.09
Brookings	April 30 (120)	11.86	11.01	11.60	11.75	11.81	11.84
Brookings	May 7 (127)	11.36	10.35	11.00	11.20	11.28	11.32
Brookings	May 14 (134)	10.44	9.54	10.17	10.36	10.41	10.40
Brookings	May 21 (141)	9.22	8.48	9.06	9.20	9.14	9.11
	Average	10.99	10.22	10.77	10.92	10.95	10.95
Boone	April 15 (105)	10.69	8.75	10.19	10.53	10.64	10.68
Boone	April 22 (112)	9.37	7.07	8.88	9.31	9.37	9.25
Boone	April 29 (119)	7.91	5.77	7.58	7.88	7.70	7.35
Boone	May 6 (126)	6.21	4.68	6.07	6.10	5.60	4.88
Boone	May 13 (133)	4.28	3.48	4.27	3.95	3.04	1.95
	Average	7.69	5.95	7.40	7.55	7.27	6.82

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.

Table 5.14. Highly risk averse[a] producer's willingness to pay ($/ac) for IPM with insurance with different EILs in Brookings and Boone over a range of plant days

		Willingness to Pay					
Location	Plant Day	EIL*	EIL=7	EIL=14	EIL=21	EIL=28	EIL=35
Brookings	April 23 (113)	12.35	11.97	12.27	12.33	12.35	12.35
Brookings	April 30 (120)	12.17	11.24	11.87	12.03	12.11	12.14
Brookings	May 7 (127)	11.73	10.57	11.27	11.51	11.62	11.66
Brookings	May 14 (134)	10.85	9.73	10.44	10.69	10.76	10.83
Brookings	May 21 (141)	9.61	8.66	9.32	9.52	9.54	9.60
	Average	11.34	10.43	11.03	11.22	11.28	11.32
Boone	April 15 (105)	11.24	9.04	10.61	11.00	11.16	11.23
Boone	April 22 (112)	9.99	7.27	9.26	9.82	9.94	9.91
Boone	April 29 (119)	8.45	5.90	7.95	8.40	8.32	8.10
Boone	May 6 (126)	6.63	4.81	6.41	6.62	6.28	5.69
Boone	May 13 (133)	4.70	3.66	4.63	4.58	3.82	2.92
	Average	8.20	6.14	7.77	8.08	7.90	7.57

[a] With a 40% risk premium and all variables stochastic. See Table 5.3.

from the fact that the partial derivative of the optimal expected utility with respect to β, the level of insurance coverage, is the covariance of the marginal utility and the marginal indemnity. In the empirical model as specified here, the lodging threshold L_{TH} is analogous to the level of coverage. A threshold of 100% implies that no insurance indemnities are ever paid—0% coverage, which is the case for producers using IPM without insurance. A lodging threshold less than 100%, such as 5% as used for the simulations here, implies some level of coverage between 0% and 100%, probably nearly 100%. The marginal utility function for CARA utility is simple to obtain. However, the indemnity schedule (5.7b) is not differentiable with respect to L_{TH}. As a result, the covariance of marginal utility and the marginal indemnity, or equivalently the derivative of optimal expected utility with respect to insurance coverage, cannot be calculated analytically from the simulation data. Rather it must be numerically approximated with differences by changing the level of coverage and noting the changes in the optimal expected utility.

Certainty equivalent returns are a monetary measure of expected utility, so that an increase in expected utility is accompanied by an increase in certainty equivalent returns. Table 5.15 reports the willingness to pay for IPM with and without insurance relative to always applying insecticide, when IPM uses the optimal EIL for each location and plant day, and the net change that IPM insurance generates. Table 5.16 does the same, but for IPM that uses a uniform EIL of 21. The reported changes are a monetarization of the changes in expected utility generated by IPM insurance when coverage is changed from no coverage (β = 0) to something greater than zero. The positive changes reported in Table 5.15 indicate that expected utility increases with insurance coverage, implying that the marginal utility and

Table 5.15. Willingness to pay (WTP) for IPM with and without actuarially fair insurance relative to always applying insecticide, when IPM uses the optimal EIL

		Moderately Risk Averse[a]			Highly Risk Averse[b]		
Location	Plant Day	WTP for IPM	WTP for IPM with Insurance	Change	WTP for IPM	WTP for IPM with Insurance	Change
Brookings	April 23 (113)	11.80	12.09	0.29	11.83	12.35	0.52
Brookings	April 30 (120)	11.55	11.86	0.31	11.61	12.17	0.56
Brookings	May 7 (127)	11.02	11.36	0.34	11.13	11.73	0.60
Brookings	May 14 (134)	10.12	10.44	0.32	10.27	10.85	0.58
Brookings	May 21 (141)	8.93	9.22	0.29	9.07	9.61	0.54
	Average	10.68	10.99	0.31	10.78	11.34	0.56
Boone	April 15 (105)	10.28	10.69	0.41	10.49	11.24	0.75
Boone	April 22 (112)	9.00	9.37	0.37	9.21	9.99	0.78
Boone	April 29 (119)	7.52	7.91	0.39	7.81	8.45	0.64
Boone	May 6 (126)	5.91	6.21	0.30	6.13	6.63	0.50
Boone	May 13 (133)	4.06	4.28	0.22	4.24	4.70	0.46
	Average	7.35	7.69	0.34	7.58	8.20	0.62

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

Table 5.16. Willingness to pay (WTP) for IPM with and without actuarially fair insurance relative to always applying insecticide, when IPM uses a uniform EIL of 21

		Moderately Risk Averse[a]			Highly Risk Averse[b]		
Location	Plant Day	WTP for IPM	WTP for IPM with Insurance	Change	WTP for IPM	WTP for IPM with Insurance	Change
Brookings	April 23 (113)	11.78	12.07	0.29	11.81	12.33	0.52
Brookings	April 30 (120)	11.45	11.75	0.30	11.49	12.03	0.54
Brookings	May 7 (127)	10.90	11.20	0.30	10.97	11.51	0.54
Brookings	May 14 (134)	10.06	10.36	0.30	10.15	10.69	0.54
Brookings	May 21 (141)	8.92	9.20	0.28	9.02	9.52	0.50
	Average	10.62	10.92	0.30	10.69	11.22	0.53
Boone	April 15 (105)	10.15	10.53	0.38	10.31	11.00	0.69
Boone	April 22 (112)	8.94	9.31	0.37	9.14	9.82	0.68
Boone	April 29 (119)	7.52	7.88	0.36	7.73	8.40	0.67
Boone	May 6 (126)	5.76	6.10	0.34	6.01	6.62	0.61
Boone	May 13 (133)	3.63	3.95	0.32	4.00	4.58	0.58
	Average	7.20	7.55	0.35	7.44	8.08	0.64

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

the marginal indemnity are positively correlated, thus satisfying the sufficient condition in Proposition 2 for actuarially fair insurance to increase producer incentives to adopt IPM. The results in Table 5.16 indicate that switching to IPM that uses a uniform EIL of 21 leaves the sign of the changes the same and the magnitudes change little. Despite this generally positive result for actuarially fair insurance, the pertinent question to address concerns actuarially feasible insurance—insurance that includes a premium load, which is addressed by Proposition 3.

The changes reported in Tables 5.15 and 5.16 are the willingness to pay for actuarially fair IPM insurance for IPM that uses either the optimal EIL or a uniform EIL. This willingness to pay is not substantial—ranging from $0.22 to $0.75 for IPM using an optimal EIL and $0.28 to $0.69 for IPM using a uniform EIL. These increases in the willingness to pay are for insurance that charges actuarially fair premiums that vary with the plant date. Table 5.17 reports these actuarially fair premiums. The premiums are higher in Boone than in Brookings and increase as the plant date increases because both these changes imply an increase in the corn rootworm population and an associated increase in corn rootworm damage and thus indemnities received.

A more realistic assumption is that insurance providers will charge a single premium that varies by location, but is uniform across plant date. Using the average premium across plant dates at both locations for this uniform premium, Table 5.18 reports the willingness to pay for IPM with insurance coverage and the associated increase in the willingness to pay due to insurance coverage. The average willingness to pay and the average increase remain essentially unchanged, but the distribution of each across plant days changes noticeably.

Using a uniform average premium increases the premiums for producers who plant early and decreases them for those who plant late. This reduces the willingness to pay for early planting producers and increases it for late planting producers, so that the overall spread

Table 5.17. Actuarially fair premiums by plant day for IPM insurance based on lodging, for IPM using a uniform EIL of 21 adults per square meter

--------- Brookings ---------		--------- Boone ---------	
Plant Day	Premium	Plant Day	Premium
April 23 (113)	2.15	April 15 (105)	2.87
April 30 (120)	2.23	April 22 (112)	3.11
May 7 (127)	2.33	April 29 (119)	3.38
May 14 (134)	2.47	May 6 (126)	3.82
May 21 (141)	2.63	May 13 (133)	4.52
Average	2.36	Average	3.54

Table 5.18. Willingness to pay (WTP) for IPM with insurance with a uniform premium equal to the average actuarially fair premium, when IPM uses a uniform EIL of 21

		Moderately Risk Averse[a]		Highly Risk Averse[b]	
Location	Plant Date	WTP	Change	WTP	Change
Brookings	April 23 (113)	12.07	0.08	12.33	0.31
Brookings	April 30 (120)	11.75	0.17	12.03	0.41
Brookings	May 7 (127)	11.20	0.27	11.51	0.51
Brookings	May 14 (134)	10.36	0.41	10.69	0.65
Brookings	May 21 (141)	9.20	0.55	9.52	0.77
	Average	10.92	0.30	11.22	0.53
Boone	April 15 (105)	10.53	-0.29	11.00	0.02
Boone	April 22 (112)	9.31	-0.06	9.82	0.25
Boone	April 29 (119)	7.88	0.20	8.40	0.51
Boone	May 6 (126)	6.10	0.62	6.62	0.89
Boone	May 13 (133)	3.95	1.30	4.58	1.56
	Average	7.55	0.35	8.08	0.65

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

in the willingness to pay across plant days is reduced relative to insurance with the variable premium. On the other hand, the increase in the willingness to pay due to insurance coverage was evenly distributed across plant days with the variable premium. However, with the uniform premium, the distribution of this increase becomes skewed to favor producers who regularly plant corn late. This skew is so severe that moderately risk averse producers in Boone have a disincentive to purchase IPM insurance charging a uniform average premium. On the other hand, the skew also increases the value of IPM for producers who plant late in Boone so that it the willingness to pay is sufficient to cover the cost of hiring a crop consultant for highly risk averse producers, and nearly so for moderately risk averse producers. Without this skew, these producers do not obtain sufficient benefits to justify adopting IPM when the costs of hiring a crop consultant are included.

However, this analysis ignores the adverse selection problem created by using this uniform average premium. Producers who regularly plant corn early will not purchase this insurance, because it does not generate sufficient risk sharing benefits for them. If they are not included in the pool of producers purchasing IPM insurance, the average premium charged to all producers is too small. However, if the average uniform premium is increased, even fewer producers will purchase IPM insurance, further exacerbating the adverse selection problem. One possible solution that is easy to implement is to require producers to purchase IPM insurance before planting has begun.

In terms of Proposition 3 and Corollary 3 from chapter 2, the changes in the willingness to pay reported in Tables 5.15, 5.16, and 5.18 are the maximum load that insurance providers can add to the respective premiums charged and still leave producers some incentive to purchase the insurance. The size of this load determines whether green insurance is actuarially feasible and thus superior to green payments at providing adoption incentives. Insurance providers use the load to cover administrative and insurance adjustment costs, as well as recover development costs and earn a normal rate of return. In general, the increases reported in these tables do not seem sufficient to pay a load on the premium and still leave producers any incentive to purchase the IPM insurance.

Consider the insurance purchase problem from the producer's perspective. The premium is essentially an investment and the increases in the willingness to pay reported in Table 5.15, 5.16, and 5.18 are the average returns to this investment. For simplicity, restrict the analysis to IPM using a uniform EIL of 21 and convert these returns to percentages of the premium charged to determine the percent return on the initial investment. Table 5.19 reports these percents for a variable premium changing with the plant day and location and a

Table 5.19. Increase in willingness to pay for IPM due to insurance coverage when IPM uses a uniform EIL of 21, expressed as a percent of the premium

		Moderately Risk Averse[a]		Highly Risk Averse[b]	
Location	Plant Date	Variable Premium	Uniform Premium	Variable Premium	Uniform Premium
Brookings	April 23 (113)	11.9	10.9	19.5	18.1
Brookings	April 30 (120)	11.9	11.3	19.5	18.6
Brookings	May 7 (127)	11.4	11.3	18.8	18.6
Brookings	May 14 (134)	10.8	11.3	17.9	18.6
Brookings	May 21 (141)	9.6	10.6	16.0	17.5
	Average	11.1	11.1	18.3	18.3
Boone	April 15 (105)	11.7	9.7	19.4	16.3
Boone	April 22 (112)	10.6	9.5	17.9	16.1
Boone	April 29 (119)	9.6	9.2	16.5	15.9
Boone	May 6 (126)	8.2	8.8	13.8	14.7
Boone	May 13 (133)	6.6	8.3	11.4	14.1
	Average	9.1	9.1	15.4	15.4

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.
[b] With a 40% risk premium and all variables stochastic. See Table 5.3.

uniform premium that is the average across all plant days, but varies by location, as reported in Table 5.17. In general these returns seem too low to encourage producers to purchase IPM insurance, particularly once the load is added to the premium. Even if the load is sufficiently small to provide on average some incentive for producers to purchase the insurance, the added adoption incentive will not be that large, only a few cents, except maybe for highly risk averse producers. In terms of Proposition 3 and Corollary 3 in chapter 2, this implies that green insurance provides little if any additional incentive to adopt corn rootworm IPM, and thus green payments are probably a better policy instrument to encourage IPM adoption.

The low value of IPM insurance to producers seems surprising given the substantial willingness to pay for IPM. However, most of the value of IPM is due to the curvature of profit in corn rootworm uncertainty, not due to the curvature of utility in profit uncertainty caused by corn rootworm uncertainty. The data in Table 5.6 indicate that generally more than 95% of the value of IPM is accounted for by the production premium, which is due to the curvature of the profit function in corn rootworm uncertainty. Utility is fairly linear in the profit uncertainty generated by corn rootworm risk because the losses occurring when IPM fails are not substantial. The potential for larger losses is needed before the curvature in utility is sufficient to generate a significant need for risk sharing. As a result, IPM provides little additional value to risk averse producers that it does not already provide to risk neutral producers. Thus, though the value of the information provided by IPM is substantial, the need for risk sharing is small for producers facing stochastic corn rootworm damage under IPM. As a result, there is a substantial willingness to pay for IPM, but a relatively small willingness to pay for IPM insurance.

This can be shown empirically with this model. Providing producers with 100% insurance coverage and charging an actuarially fair premium stabilizes corn rootworm losses at their mean and completely removes uncertainty due to corn rootworm. In the model here, this can be accomplished by setting the root rating threshold at 1 and the lodging threshold at 0%. Simulations of this sort were used to determine the willingness to pay to fix corn rootworm losses at their mean and indicate the need for risk sharing. Table 5.20 reports the resulting willingness to pay relative to the status quo practice of always applying insecticide and the increase this represents over IPM using a uniform EIL of 21.

The total willingness to pay is relatively large, but the increase in willingness to pay generated by fixing corn rootworm losses at their mean is small. As a result, even if a perfect insurance signal were available so that all corn rootworm risk when using IPM could be

Table 5.20. Highly risk averse[a] producer's willingness to pay (WTP) to stabilize corn rootworm losses at their mean and the resulting increase relative to the willingness to pay for IPM without insurance using a uniform EIL of 21

------------ Brookings ------------			------------ Boone ------------		
Plant Day	WTP	Increase	Plant Day	WTP	Increase
April 23 (113)	12.28	0.46	April 15 (105)	10.92	0.61
April 30 (120)	11.97	0.47	April 22 (112)	9.74	0.60
May 7 (127)	11.45	0.48	April 29 (119)	8.33	0.60
May 14 (134)	10.63	0.47	May 6 (126)	6.56	0.55
May 21 (141)	9.46	0.44	May 13 (133)	4.52	0.52
Average	11.16	0.47	Average	8.01	0.58

[a] With a 40% risk premium and all variables stochastic. See Table 5.3.

eliminated with complete insurance, this insurance would not have great value to producers relative to IPM alone.

This result still does not resolve the paradox of corn rootworm IPM—why do few producers adopt IPM when it seems to have obvious value? Originally it was hoped that the analysis here would find that IPM was still "risky," thus explaining the paradox, and that IPM insurance could play a role as a possible remedy. However, the results indicate that IPM is not risky and that it removes most of the uncertainty in profit due to corn rootworm losses, which only confirms the original paradox. Despite its complexity, this model is still highly stylized and does not capture many important factors in the adoption decision. Nowak (1992) reviews several that may be relevant to corn rootworm IPM, including lacking or conflicting information, lack of locally available supporting resource (such as a reputable crop consultant), and the belief in traditional practices that many producers hold. In addition, agricultural chemical companies have large advertising budgets to encourage the regular use of pesticides, including soil insecticides. Because the value of IPM to producers is relatively large, there is potential for those "selling" IPM, including insurance companies, to extract part of this rent. As a result, IPM insurance may have a role in encouraging producers to adopt corn rootworm IPM. In the final analysis, stylized economic models will have to be put aside and the IPM insurance concept will have to be tested in the field—will real farmers buy real IPM insurance at the offered price?

5.5.2 Impact of IPM Insurance on Optimal Insecticide Use

Chapter 2 presented three propositions concerning the impact of green payments and green insurance on optimal input use. In Proposition 4, decreasing absolute risk aversion is among the conditions for the wealth effect caused by green payments to affect optimal input use. However, constant absolute risk aversion is assumed in the model used here, so that the wealth effect must be zero. Similarly, the moral hazard effect developed in Proposition 6 cannot occur in the model used here. By assumption, producers cannot affect the distribution function of the insurance signal—lodging—if they do not apply insecticide, and producers can only purchase IPM insurance when they do not apply insecticide. Lastly, Proposition 5 concerned the risk effect, the impact of green insurance coverage on optimal input use. If producers use the same uniform EIL with and without IPM insurance, actual use of insecticide will not change as a result of insurance coverage. Optimal insecticide use only decreases as a result of the adoption effect, for which it was not possible to derive a proposition. However, Proposition 5 applies to optimal insecticide use, not actual insecticide use. As a result, the sign and magnitude of the risk effect can be determined empirically and compared to results obtained by other researchers for insecticide.

Table 5.21 reports the optimal EIL and associated insecticide application rate with and without IPM insurance for a moderately risk averse producer, while Table 5.22 does the same for a highly risk averse producer. For both locations and for all plant dates the optimal

Table 5.21. Effect of IPM insurance on the optimal EIL and the insecticide application rate (expressed as a percent of the status quo rate) for a moderately risk averse[a] producer

		No Insurance		With Insurance	
Location	Plant Day	EIL	Rate	EIL	Rate
Brookings	April 23 (113)	100.0	0.0	100.0	0.0
Brookings	April 30 (120)	100.0	0.0	100.0	0.0
Brookings	May 7 (127)	45.5	1.4	50.5	1.1
Brookings	May 14 (134)	28.0	7.1	28.0	6.9
Brookings	May 21 (141)	23.0	15.1	25.0	14.5
	Average	59.3	4.7	60.7	4.5
Boone	April 15 (105)	34.0	1.7	34.5	1.6
Boone	April 22 (112)	24.5	9.7	25.0	9.4
Boone	April 29 (119)	21.0	20.3	22.5	19.3
Boone	May 6 (126)	18.0	32.9	19.0	32.1
Boone	May 13 (133)	13.5	49.5	14.0	49.0
	Average	22.2	22.8	23.0	22.3

[a] With a 20% risk premium and all variables stochastic. See Table 5.3.

Table 5.22. Effect of IPM insurance on the optimal EIL and the insecticide application rate (expressed as a percent of the status quo rate) for a highly risk averse[a] producer

		No Insurance		With Insurance	
Location	Plant Day	EIL	Rate	EIL	Rate
Brookings	April 23 (113)	100.0	0.0	100.0	0.0
Brookings	April 30 (120)	100.0	0.0	100.0	0.0
Brookings	May 7 (127)	51.0	1.1	68.5	0.5
Brookings	May 14 (134)	29.5	6.8	41.5	5.0
Brookings	May 21 (141)	25.5	14.3	30.5	12.7
	Average	35.3	7.4	46.8	6.1
Boone	April 15 (105)	34.5	1.6	35.5	1.5
Boone	April 22 (112)	25.5	9.2	31.5	7.5
Boone	April 29 (119)	23.0	18.9	23.5	18.8
Boone	May 6 (126)	19.5	31.3	20.0	31.7
Boone	May 13 (133)	15.0	47.7	16.5	46.2
	Average	61.2	4.4	68.1	3.6

[a] With a 40% risk premium and all variables stochastic. See Table 5.3.

EIL increases, and thus the optimal application rate decreases. This indicates that soil insecticides for corn rootworm control are a risk reducing input for corn producers in these areas. This result agrees with the conventional finding that total expenditures on chemical inputs (fertilizer and pesticides) decrease when producers purchase crop insurance (Smith and Goodwin 1996, Babcock and Hennessy 1996, Quiggin et al. 1993).

5.6 Summary of Empirical Findings

This long chapter presented several empirical findings derived from the Monte Carlo simulations, some of which are related to the theoretical results presented in chapter 2. These findings are summarized here:

1) Corn rootworm IPM has value to producers who annually apply soil insecticides, on average around $10 per acre in Brookings and a little less than $7.50 per acre in Boone. This value is sufficient to cover the cost of hiring a crop consultant to provide corn rootworm IPM recommendations along with other services.
2) Adoption of IPM reduces the frequency of insecticide applications substantially. On average producers using IPM in Brookings optimally apply insecticide only about 5% of the time, while in Boone the frequency is 20%-25%.
3) Relative to using an EIL that varies optimally with the plant day and location, a uniform EIL of 21 adults per square meter (about 3 adults per plant) captures most of the value of IPM with little change in the frequency of insecticide application.
4) The optimal variable and uniform EILs derived here are higher than those typically recommended by entomologists. This difference may be due to several factors, including model error and only including one corn rootworm species. However, the recommended

EIL may not be expected profit or utility maximizing, but rather concerned with reducing the probability of readily observable IPM failures to acceptable levels.

5) Lodging is a better measure than root ratings for the yield loss occurring as a result of corn rootworm damage. However, this does not imply that root ratings are not effective measures of corn rootworm damage.

6) IPM insurance, charging actuarially fair premiums that vary with plant day, has value to risk averse producers—on average about $0.30 to $0.65 per acre. These actuarially fair premiums range from $2.15 to $2.63 in Brookings and from $2.87 to $4.52 in Boone. If a uniform premium averaging across planting dates is used, the average value of IPM insurance remains about $0.30 to $0.65 per acre, but producers who regularly plant corn early have little incentive, or have disincentives, to purchase IPM insurance.

7) Once a load is added to the premium to make IPM insurance actuarially feasible, the remaining willingness to pay probably will not be sufficient to encourage producers to purchase IPM insurance. As a policy instrument to encourage IPM adoption, IPM insurance will only dominate a green payment subsidy if factors not modeled here are reduced more by actuarially feasible insurance than by the subsidy.

8) Losses associated with IPM failure are not substantial. As a result, risk sharing needs for producers using IPM are not significant and thus IPM insurance has little value to producers.

9) Soil insecticides for corn rootworm control are risk reducing inputs, which agrees with the conventional finding concerning chemical inputs such as pesticides.

REFERENCES

Agricultural Conservation Innovation Center (ACIC). 1998a. Promoting conservation innovation in agriculture through crop insurance. ACIC, <www.agconserv.com/risk.html>.

Agricultural Conservation Innovation Center (ACIC). 1998b. Summary of project activities: status reports. ACIC, <www.agconserv.com/Acomplish.html>.

Allen, J. C. 1976. A modified sine wave method for calculating degree days. Environ. Entomol. 5(3): 388-396.

Antle, J. M. Incorporating risk in production analysis. 1983. Amer. J. Ag. Econ. 66(10): 1099-1106.

Arnold, C. Y. 1960. Maximum-minimum temperatures as a basis for computing heat units. Proc. Am. Soc. Hort. Sci. 76: 682-692.

Babcock, B. A., T. Campbell, P. Gassman, T. M. Hurley, P. D. Mitchell, T. Otake, M. Siemers, and J. Wu. 1997. *RAPS 1997: Agricultural and Environmental Outlook.* Center for Agricultural and Rural Development, Iowa State University, Ames, IA.

Babcock, B. A., A. L. Carriquiry, and H. S. Stern. 1996. Evaluation of soil test information in agricultural decision-making. App. Stat. 45(4): 447-461.

Babcock, B. A., J. A. Chalfant, and R. N. Collender. 1987. Simultaneous input demands and land allocation in agricultural production under uncertainty. West. J. Ag. Econ. 12(2): 207-215.

Babcock, B. A., E. K. Choi, and E. Feinerman. 1993. Risk and probability premiums for CARA utility functions. J. Ag. Res. Econ. 18(1): 17-24.

Babcock, B. A., and D. A. Hennessy. 1996. Input demand under yield and revenue insurance. Amer. J. Ag. Econ. 78(2): 416-427.

Babcock, B. A., and J. F. Shogren. 1995. The cost of agricultural production risk. Ag. Econ. 12: 141-150.

Becker, R., and H. Stockdale. 1980. Pesticides used in Iowa crop production in 1978 and 1979. Pamphlet Pm-964, Iowa Coop. Ext. Serv., Ames.

Benoit, G. R., and K. A. Van Sickle. 1991. Overwintering soil temperature patterns under six tillage-residue combinations. Trans. Am. Soc. Ag. Eng. 34(1): 86-90.

Berndt, E. K., B. H. Hall, R. E. Hall, and J. A. Hausman. 1974. Estimation and inference in nonlinear structural models. Ann. Econ. Social Measure. 3: 653-665.

Blackmer, A. M., and A. P. Mallarino. 1996. Cornstalk testing to evaluate nitrogen management. PM-1584, Iowa State University Extension, Ames.

Braden, J. B., N. R. Netusil, and R. F. Kosobud. 1994. Incentive-based nonpoint source pollution abatement in a reauthorized Clean Water Act. Wat. Res. Bull. 30(5): 781-791.

Bystrom, O., and D. W. Bromley. 1998. Contracting for nonpoint-source pollution abatement. J. Ag. Res. Econ. 23(1): 39-54.

Calkins, C. O., and V. M. Kirk. 1969. Effect of winter precipitation and temperature on overwintering eggs of northern and western corn rootworms. J. Econ. Entomol. 62(3): 541-543.

Chavas, J. P., and M. T. Holt. 1996. Economic behavior under uncertainty: a joint analysis of risk preferences and technology. Rev. Econ. Statist. 78(???): 329-35.

Cheng, R. C. H. 1998. Random variate generation, p. 139-172. In J. Banks (ed.) Handbook of simulation: principles, methodology, advances, applications and practice. John Wiley, New York.

Chiang, H. C. 1965. Survival of northern corn rootworm eggs through one and two winters. J. Econ. Entomol. 58:470-472.

Chiang, H. C. 1973. Bionomics of the northern and western corn rootworms. Annu. Rev. Entomol. 18: 47-72.

Cooper, J. C., and R. W. Keim. 1996. Incentive payments to encourage farmer adoption of water-quality protection practices. Amer. J. Ag. Econ. 78(1): 54-64.

Davis, P. M., N. Brenes, and L. L. Allee. 1991. Temperature dependent models to predict regional differences in corn rootworm (Coleoptera: Chrysomelidae) phenology. Environ. Entomol. 25(4): 767-775.

EarthInfo. 1996. EarthInfo CD^2. Boulder, CO.

Edwards, C. R., L. W. Bledsoe, and J. L. Obermeyer. 1999. Managing corn rootworms—1999. Field Crops E-49, Purdue Univ. Coop. Ext. Serv., West Lafayette.

Elliot, N. C., G. R. Sutter, T. F. Branson, and J. R. Fisher. Effect of population density of immatures on survival and development of the western corn rootworm (Coleoptera: Chrysomelidae). J. Entomol. Sci. 24(2): 209-213.

Evans, M., N. Hastings, and B. Peacock. 1993. Statistical distributions, 2nd ed. John Wiley, New York.

Farham, D. E. 1997. Is it too early to plant corn? Integrated Crop Management Newsletter. Iowa State University Extension. Apr. 21: 40-41

Fisher, J. R. 1986. Development and survival of pupae of *Diabrotica virgifera virgifera* and *D. undecimpunctata howardi* (Coleoptera Chrysomelidae) at constant temperatures and humilities. Environ. Entomol. 15(3): 626-630.

Fisher, J. R. 1989. Hatch of *Diabrotica virgifera virgifera* (Coleoptera: Chrysomelidae) eggs exposed to two different overwintering and hatch regimes. J. Kan. Entomol. Soc. 62(4): 607-610.

Foster, R. E., and J. J. Tollefson. 1986. Frequency and severity of attack of several pest insects on corn in Iowa. J. Kansas Entomol. Soc. 59:269-274.

Foster, R. E., J. J. Tollefson, J. P. Nyrop, and G. L. Hein. 1986. Value of adult corn rootworm (Coleoptera: Chrysomelidae) population estimates in pest management decision making. J. Econ. Entomol. 79: 303-310.

Freund, J. E. 1992. Mathematical Statistics, 5th ed. Prentice Hall, Englewood Cliffs, NJ.

Gerber, C., C. R. Edwards, L. W. Bledsoe, M. E. Gray, K. L. Steffey. 1999. Application of the areawide concept for managing western corn rootworm in the Eastern Midwest corn/soybean cropping system. Presented at the North Central Branch of the Entomological Society of America's annual meetings, Des Moines, IA, March 28-31.

Gray, M. E., E. Levine, and K. L. Steffey. 1996. Western corn rootworms and crop rotation: have we selected a new strain? p. 653-660. *In* Proceedings of Brighton Crop Protection Conference, British Crop Protection Council, Brighton, UK.

Gray, M. E., and K. L. Steffey. 1998. Corn rootworm (Coleoptera: Chrysomelidae) larval injury and root compensation of 12 maize hybrids: an assessment of the economic injury index. J. Econ. Entomol. 91:723-740.

Greene, W. H. 1997. Econometric analysis, 3rd ed. Prentice Hall, Upper Saddle River, NJ.

Griffin, R. C., and D. W. Bromley. 1982. Agricultural runoff as a nonpoint externality: a theoretical development. Amer. J. Ag. Econ. 65(3): 547-552.

Griffin, S. 1999. Personal communication. IGF Insurance, Des Moines, IA.

Gupta, S. C., W. E. Larson, and D. R. Linden. 1983. Tillage and surface residue effects on soil upper boundary temperatures. Soil Sci. Soc. Am. J. 47: 1212-1218.

Gupta, S. C., J. K. Radke, and W. E. Larson. 1981. Predicting temperatures of bare and residue covered soils with and without a corn crop. Soil Sci. Soc. Am. J. 45: 405-412.

Gustin, R. D. 1981. Soil temperature of overwintering western corn rootworm eggs. Environ. Entomol. 10(4): 483-487.

Havlin, J. L., D. E. Kissel, L. D. Maddux, M. M. Claassen, and J. H. Long. 1990. Crop rotation and tillage effects on soil organic carbon and nitrogen. Soil Sci. Soc. Am. J. 54: 448-452.

Hein, G. L., and J. J. Tolefson. 1987. Model of the biotic potential of western corn rootworm (Coleoptera: Chrysomelidae) adult populations, and its use in studying population dynamics. Environ. Entomol. 16(2): 446-452.

Helfand, G. E., and B. W. House. 1995. Regulating nonpoint source pollution under heterogeneous conditions. Amer. J. Ag. Econ. 77(4): 1024-1032.

Hennessy, David A. 1998. The production effects of agricultural income support policies under uncertainty. Amer. J. Ag. Econ. 80(1): 46-57.

Hennessy, D. A., B. A. Babcock, and D. J. Hayes. 1997. Budgetary and producer welfare effects of revenue insurance. Amer. J. Agric. Econ. 79(3): 1024-1034.

Hennessy, D. A., and B. A. Babcock. 1998. Information, flexibility, and value added. Inform. Econ. Policy 10:431-449.

Herriges, J. A., R. Govindasamy, and J. F. Shogren. 1994. Budget-balancing incentive mechanisms. J. Environ. Econ. Manage. 27(3): 275-285.

Higley, L. G., L. P. Pedigo, and K. R. Ostlie. 1986. DEGDAY: A program for calculating degree-days, and assumptions behind the degree-day approach. Environ. Entomol. 15(5): 999-1016.

Hirshleifer, J., and J. G. Riley. 1992. The analytics of uncertainty and information. Cambridge: Cambridge University Press.

Hoag, D. L., and J. S. Hughes-Popp. 1997. Theory and practice of pollution credit trading in water quality management. Rev. Ag. Econ. 19(2): 252-262.

Holmstrom, B. 1982. Moral hazard in teams. Bell J. Econ. 13(2): 323-340.

Horowitz, J. K., and E. Lichtenberg. 1993. Insurance, moral hazard, and chemical use in agriculture. Amer. J. Ag. Econ. 75(4): 926-935.

Iowa State University Extension. 1998. Estimated costs of crop production in Iowa. ISU Univ. Ext., Ames, IA.

Jackson, J. J., and N. C. Elliot. 1988. Temperature-dependent development of immature stages of the western corn rootworm, *Diabrotica virgifera virgifera* (Coleoptera: Chrysomelidae). Environ. Entomol. 17(2): 166-171.

Just, R. E. 1975. Risk aversion under profit maximization. Amer. J. Ag. Econ. 58(2): 347-352.

Just, R. E., and R. D. Pope. 1978. Stochastic specification of production functions and economic implications. J. Econometrics. 7: 67-86.

Just, R. E., and R. D. Pope. 1979. Production function estimation and related risk considerations. Amer. J. Ag. Econ. 62(2): 276-284.

Krysan, J. L. 1986. Introduction: biology, distribution, and identification of pest *Diabrotica*. p. 1-24. In J. L. Krysan and T. A. Miller (eds.), Methods for the study of pest *Diabrotica*. Springer-Verlag, New York.

Krysan, J. L., J. J. Jackson, and A. C. Lew. 1984. Field termination of egg diapause in *Diabrotica* with new evidence of extended diapause in *D. barberi* (Coleoptera: Chrysomelidae). Environ. Entomol. 13: 1237-1240.

Larson, W. E., R. F. Holt, and C. W. Carlson. 1978. Residues for soil conservation. p. 1-15. *In* W. R. Oschwald (ed.) Crop residue management systems. ASA Spec. Publ. 31. ASA, CSSA, SSSA, Madison, WI.

Leland, H. E. 1972. Theory of the firm facing uncertain demand. Amer. Econ. Rev. 62: 278-291.

Lial, M. L., R. N. Greenwell, and C. D. Miller. 1998. Finite mathematics, 6th ed. Addison-Wesley, Reading, MA.

Loehman, E., and C. Nelson. 1992. Optimal risk management, risk aversion, and production function properties. J. Ag. Res. Econ. 17(2): 219-231.

Logan, J. A., R. E. Stinner, R. L. Rabb, and J. S. Bacheler. 1979. A descriptive model for predicting spring emergence of *Heliothis zea* populations in North Carolina. Environ. Entomol. 8(1): 141-146.

Love, H. A., and S. T. Bucola. 1991. Joint risk preference-technology estimation with a primal system. Amer. J. Ag. Econ. 74(3): 765-774.

MacMinn, R. D., and A. G. Holtmann. 1983. Technological uncertainty and the theory of the firm. S. Econ. J. 50: 120-136.

Malik, A. S., B. A. Larson, and M. Ribaudo. 1994. Economic incentives for agricultural nonpoint source pollution control. Wat. Res. Bull. 30(3): 471-480.

Malik, A. S., D. Letson, and S. R. Crutchfield. 1993. Point/nonpoint source trading of pollution abatement: choosing the right trading ratio. Amer. J. Ag. Econ. 75(3): 959-967.

Marschak, J. 1954. Towards an economic theory of organization and information. *In* Thrall, R. M., C. H. Coombs, and R. L. Davies (eds.). Decision Processes, Wiley, New York.

Matalas, N. C. 1967. Mathematical assessment of synthetic hydrology. Water Resourc. Res. 3(4): 937-945.

Mayo, Z. B., Jr. 1986. Field evaluation of insecticides for control of larvae of corn rootworms. *In* J. L. Krysan and T. A. Miller (eds.), Methods for the study of pest *Diabrotica*. pp. 183-203. Springer-Verlag, New York.

Metcalf, R. L. 1986. Forward. *In* J. L. Krysan and T. A. Miller (eds.), Methods for the study of pest *Diabrotica*. pp. vii-xv. Springer-Verlag, New York.

Michigan State University Extension. 1998. Special corn rootworm issue. Crop Advisory Team Alert. Vol. 13, No. 12. Lansing, Michigan.

Mitchell, G., R. H. Griggs, V. Benson, and J. R. Williams. 1997. EPIC user's guide-draft, version 5300. Tex. Ag, Exp. Stn., Temple, TX.

Mooney, E., and F. T. Turpin. 1976. ROWSIM: a GASP IV based rootworm simulator. Research Bulletin 938, Purdue Ag. Exp. Stn., West Lafayette, IN.

Mullock, B. S., C. R. Ellis, and G. H. Whitfield. 1995. Evaluation of an oviposition trap for monitoring egg populations of Diabrotica spp. (Coleoptera: Chrysomelidae) in field corn. Can. Ent. 127: 839-849.

Naranjo, S. E., and A. J. Sawyer. 1987. Reproductive biology and survival of *Diabrotica barberi* (Coleoptera: Chrysomelidae): effect of temperature, food, and seasonal time of emergence. Ann. Entomol. Soc. Am. 80(6): 841-848.

Naranjo, S. E., and A. J. Sawyer. 1988a. A temperature- and age-dependent model of reproduction for the northern corn rootworm, *Diabrotica barberi* Smith and Lawrence (Coleoptera: Chrysomelidae). Can. Ent. 120: 1-17.

Naranjo, S. E., and A. J. Sawyer. 1988b. Impact of host plant phenology on the population dynamics and oviposition of northern corn rootworms, *Diabrotica barberi* (Coleoptera: Chrysomelidae), in field corn. Environ. Entomol. 17(3): 508-521.

Naranjo, S. E., and A. J. Sawyer. 1989a. A simulation model of northern corn rootworm, *Diabrotica barberi* Smith and Lawrence (Coleoptera: Chrysomelidae), population dynamics and oviposition: significance of host plant phenology. Can. Ent. 121: 169-191.

Naranjo, S. E., and A. J. Sawyer. 1989b. Analysis of a simulation model of northern corn rootworm, *Diabrotica barberi* Smith and Lawrence (Coleoptera: Chrysomelidae), dynamics in field corn, with implications for population management. Can. Ent. 121: 193-208.

Nelson, C. H., and P. V. Preckel. 1989. The conditional beta distribution as a stochastic production function. Am. J. Agric. Econ. 71(2): 370-378.

Nowak, P. 1992. Why farmers adopt production technology. J. Soil Wat. Conserv. 47: 14-16.

Oleson, J. D. 1998. Node-injury root rating scale. p. 9-11. *In* J. J. Tollefson. 1998 Corn insecticide evaluations. Iowa State University Dept. Entomol., Ames, IA.

Pike, D. R., K. D. Glover, E. L. Knake, and D. E. Kuhlman. 1991. Pesticide use in Illinois: results of a 1990 survey of major crops. Circ. DP-91-1, Coop. Ext. Serv. Univ. Illinois, Urbana-Champaign.

Pike, D. R., K. L. Steffey, M. E. Gray, H. W. Kirby, D. I. Edwards, and R. H. Hornbaker. 1995. Biological and economic assessment of pesticide use on corn and soybeans. Report 1-CA-95. USDA-National Agricultural Pesticide Impact Assessment Program, Washington, DC.

Pope, R. D., and R. A. Kramer. 1979. Production uncertainty and factor demands for the competitive firm. S. Econ. J. 46: 489-501.

Potter, K. N., and J. R. Williams. 1994. Predicting daily mean soil temperatures in the EPIC simulation model. Agron. J. 86: 1006-1011.

Pratt, J. W. 1964. Risk aversion in the small and in the large. Econometrica. 32(1-2): 122-136.

Press, W. H., S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery. 1992. Numerical recipes in C++: the art of scientific computing, 2nd ed. Cambridge University Press, Cambridge.

Quiggin, J. 1991. Comparative statics for rank dependent expected utility theory. J. Risk Uncert. 4: 339-350.

Quiggin, J., G. Karagiannis, and J. Stanton. 1993. Crop insurance and crop production: an empirical study of moral hazard and adverse selection. Austral. J. Ag. Econ. 37(2): 95-113.

Ramaswami, B. 1992. Production risk and optimal input decisions. Amer. J. Ag. Econ. 74(4): 860-869.

Ramaswami, B. 1993. Supply response to agricultural insurance: risk reduction and moral hazard effects. Amer. J. Ag. Econ. 75(4):914-925.

Rasmusen, E. 1987. Moral hazard in risk-averse teams. RAND J. Econ. 18: 428-435.

Ratti, R. A., and A. Ullah. 1976. Uncertainty in production and the competitive firm. S. Econ. J. 43: 703-710.

Richardson, C. W. 1981. Stochastic simulation of daily precipitation, temperature, and solar radiation. Water Resour. Res. 17(1): 182-190.

Rice, M. E. 1997. Performance of corn rootworm insecticides. Integrated Crop Management Newsletter, Iowa State University Extension. Feb 3: 1-2.

Riedell, W. E., T. E. Schumacher, and P. D. Evenson. 1996. Nitrogen fertilizer management to improve crop tolerance to corn rootworm larval feeding damage. Agron. J. 88(1): 27-32.

Ritchie, S. W., and J. J. Hanway. 1982. How a corn plant develops. Iowa Coop. Ext. Serv. Special Report 48.

Saha, A., C. R. Shumway, and H. Talpaz. 1994. Joint estimation of risk preference structure and technology using expo-power utility. Am. J. Agric. Econ. 76(2):173-184.

Schaafsma, A. W., G. H. Whitfield, and C. R. Ellis. 1991. A temperature-dependent model of egg development of the western corn rootworm, *Diabrotica virgifera virgifera* Leconte (Coleoptera: Chrysomelidae). Can. Ent. 123: 1183-1197.

Segerson, K. 1988. Uncertainty and incentives for nonpoint pollution control. J. Environ. Econ. Manag. 15: 87-98.

Shortle, J. S., and J. W. Dunn. 1986. The relative efficiency of agricultural source water pollution control policies. Amer. J. Agric. Econ. 69(3): 668-677.

Smith, V. H., and B. K. Goodwin. 1996. Crop insurance, moral hazard, and agricultural chemical use. Amer. J. Agric. Econ. 78(2): 428-438.

South Dakota State University Extension Economics. 1998. South Dakota Crop and Livestock Budgets. SDSU Econ. Dept., Brookings, SD.

Spike, B. P., and J. J. Tollefson. 1989. Relationship of plant phenology to corn yield loss resulting from western corn rootworm (Coleoptera: Chrysomelidae) larval injury, nitrogen deficiency, and high plant density. J. Econ. Entomol. 82(1): 226-231.

Spike, B. P., and J. J. Tollefson. 1991. Yield response of corn subjected to western corn rootworm (Coleoptera: Chrysomelidae) infestation and lodging. J. Econ. Entomol. 84(5): 1585-1590.

Stamm, D. E., Z. B. Mayo, J. B. Campbell, J. F. Witkowski, L. W. Andersen, and R. Kozub. 1985. Western corn rootworm (Coleoptera: Chrysomelidae) beetle counts as a means of making larval control recommendations in Nebraska. J. Econ. Entomol. 78(4):794-798.

Tollefson, J. J. 1998. 1998 Corn insecticide evaluations. Iowa State University Dept. Entomol., Ames, IA.

TSP International. 1995. Time Series Processor, version 4.3. Palo Alto, CA.

Tweeten, L., and C. Zulauf. 1997. Public policy for agriculture after commodity programs. Rev. Agric. Econ. 19(1): 263-280.

United States Department of Agriculture. 1979. Weights, measures, and conversion factors for agricultural commodities and their products. Agriculture Handbook No. 697. USDA-ERS, Washington, DC.

U.S. Environmental Protection Agency and U.S. Department of Agriculture (USEPA/USDA). 1990. National Water Quality Inventory, 1990 Report to Congress. Washington, DC.

Varvel, G. E., J. S. Schepers, and D. D. Francis. 1997. Chlorophyll meter and stalk nitrate techniques as complementary indices for residual nitrogen. J. Prod. Agric. 10(1): 147-151.

Westra, J., and K. Olson. 1997. Farmers' decision processes and adoption of conservation tillage. Department of Applied Economics Staff Paper P97-9, University of Minnesota, St. Paul.

Williams, J. R. 1995. The EPIC model. p. 909-1000. *In* V. P. Singh (ed.) Computer models of watershed hydrology. Water Resources Publications, Highlands Ranch, CO.

Wolf, A. T. 1995. Rural nonpoint source pollution control in Wisconsin: the limits of a voluntary program? Water Resourc. Bull. 31: 1009-1022.

Woodson, W. D. 1993. Effect of species composition on the survival and development of western and northern corn rootworm (Coleoptera: Chrysomelidae). J. Kan. Entomol. Soc. 66(4): 377-382.

Woodson, W. D. 1994. Interspecific and intraspecific larval competition between *Diabrotica virgifera virgifera* and *Diabrotica barberi* (Coleoptera: Chrysomelidae). Environ. Entomol. 23(3): 612-616.

Woodson, W. D., and M. M. Ellsbury. 1994. Low temperature effects on hatch of northern corn rootworm eggs (Coleoptera: Chrysomelidae). J. Kan. Entomol. Soc. 67(1): 102-106.

Woodson, W. D., and J. J. Jackson. 1996. Development rate as a function of temperature in northern corn rootworm (Coleoptera: Chrysomelidae). Ann. Entomol. Soc. Am. 89(2): 226-230.

Woodson, W. D., J. J. Jackson, and M. M. Ellsbury. 1996. Northern corn rootworm (Coleoptera: Chrysomelidae) temperature requirements for egg development. Ann. Entomol. Soc. Am. 89(6): 898-903.

Woolhiser, D. A., and G. G. S. Pegram. 1979. Maximum likelihood estimation of Fourier coefficients to describe seasonal variations of parameters in stochastic daily precipitation models. J. Appl. Meteor. 18: 34-42.

Xepapadeas, A. P. 1991. Environmental policy under imperfect information: incentives and moral hazard. J. Environ. Econ. Manag. 20: 113-126.

Xepapadeas, A. P. 1992. Environmental policy design and dynamic nonpoint-source pollution. J. Environ. Econ. Manag. 23: 22-39.